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To Buy or Not to Buy?

Price Salience in an Online Shopping Field Experiment*

Markus Dertwinkel-Kalt, Mats Köster, and Matthias Sutter

April 2020

Abstract

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 initiate a purchase process for a 3D movie more often when the 3D surcharge is shrouded, but they also drop out more often when the overall price is shown at the check-out. In sum, the demand distribution is independent of the price presentation. This result qualifies previous findings on the effectiveness of shrouding surcharges and can be rationalized through low cancellation costs.

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, for which reason the presentation and salience of prices can affect their purchasing behavior and should be taken into consideration by policy-makers (see Bernheim and Taubinsky, 2018, or Gabaix, 2019).[1] Yet, in order to design optimal policies in the presence of inattentive consumers, it is necessary to know how and under which circumstances inattention and price (non-)salience matter for consumption behavior.

We conduct a natural field experiment to answer the question whether the (initial) salience of a surcharge affects demand even if it is costless to cancel the purchase process once the full price (including the surcharge) is shown at the check-out. Precisely, we examine whether shrouding or partitioning a surcharge just at the beginning of the purchase process increases demand or whether presenting the full price on the confirmation screen de-biases inattentive consumers. In contrast to previous studies (e.g., Chetty et al., 2009; Feldman and Ruffle 2015; Blake et al., 2018), our experimental design reduces potential frictions that make it costly to cancel an initiated purchase process – e.g., social image concerns, the attachment effect, the sunk-cost fallacy, or actual re-optimization costs – by as much as possible, thereby maximizing the scope to de-bias inattentive consumers (for a detailed literature review see Section 5).

In cooperation with a large German cinema, we ran a natural field experiment from April 2017 to January 2018. During this period, we manipulated the presentation of prices for 3D movies in the cinema's online store. These prices consist of a base price, which varies across movies and days, plus a fixed 3D surcharge of 3 Euro. We implemented three treatments by presenting either (i) the full price including the 3D surcharge (i.e., *Inclusive*), (ii) the base price with a small footnote indicating that an additional 3D surcharge has to be paid (i.e., *Shrouded*), or (iii) the base price and the 3D surcharge separately (i.e., *Partitioned*). In all three treatments, prior to confirming the purchase, consumers were presented the full price (including the surcharge) at the check-out. We can thus examine whether our treatments have an impact on a consumer's likelihood to (1) proceed to the check-out and (2) actually buy the product. Examining both parts of the purchase process separately allows us to study whether consumers who initiated the purchase process only due to the manipulation of the price presentation can be de-biased by presenting the full price (including the surcharge) prior to the purchase.

[1] Several countries – including the U.S., the U.K., and Germany – invest in consumer protection to prevent firms from exploiting unsophisticated consumers, and some countries (such as the U.S. or the U.K.) have even implemented "behavioral insights" teams to improve government policies based on psychologically more realistic views of consumption behavior.

Tracking more than 34,000 consumers over a period of 9 months, we find that shrouding the 3D surcharge significantly increases the likelihood that a consumer initiates a purchase process for a 3D movie. Under the assumption that inattention to shrouded surcharges is independent of the consumption value of a 3D movie, we estimate that more than 10% of the consumers neglect the shrouded fee in the beginning. While this finding is in line with the existing empirical literature, we also find that shrouding does *not* affect actual purchases. This null-result arises from consumers in *Shrouded* dropping out much more likely once they see the full price (including the surcharge) at the check-out. We conclude that in our setup consumers can be de-biased by presenting them the full price before they complete the purchase, which suggests that shrouding effects depend on the shopping environment. Partitioning prices without shrouding the surcharge, in contrast, does neither affect the likelihood to initiate nor the likelihood to complete a purchase process.

The rest of the paper is organized as follows. In Section 2 we introduce our experimental design. Section 3 presents our main results. Section 4 provides evidence on the mechanism. Section 5 positions our findings into the related literature. Section 6 concludes the paper.

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 room within the same multiplex at a potentially different time.

Purchase process. The purchase process in the cinema's online store consists of four steps, as illustrated in Figure 1: First, the consumer browses the cinema schedule (see Figure C.1 in the Appendix for a screenshot), which includes all shows running in the next 7 days. After selecting a certain show, the consumer has to log in with an email address and a password. Then, on a first screen, the consumer observes, depending on the treatment, either the full price (including the surcharge), or only the base price, or both price components, and selects the number of tickets that she would like to buy for this particular show. We say that the consumer *initiates* the purchase process if she proceeds to the second screen, where in all treatments the full price is presented and the consumer has to enter her payment details. On a third screen, all relevant information is summarized and the consumer has to finally confirm the purchase. We say that the consumer *completes* the purchase if she confirms on the third screen.

Figure 1. *Purchase process.*

Browse the movie schedule and select a movie show.

↓ Log in with an email address.

1. Screen: select the number of tickets.

↓ *Initiate* the purchase process.

2. Screen: observe full price and enter the payment details.

↓

3. Screen: review and confirmation.

↓ *Complete* the purchase process.

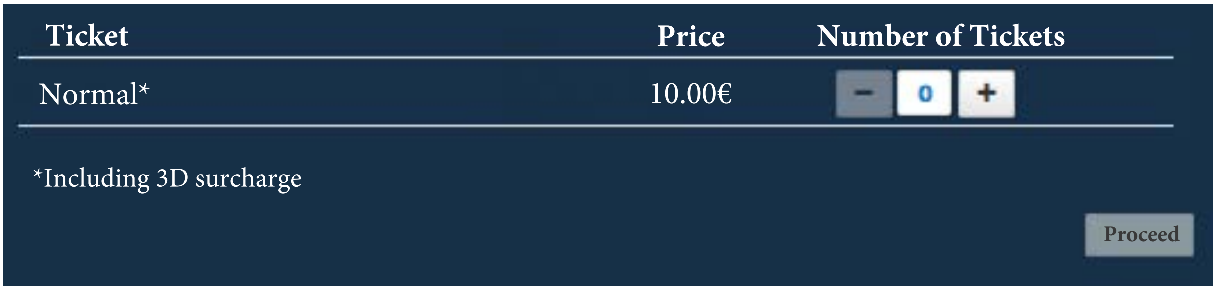
Watch the movie.

The main feature of our experiment is that the treatment variation concerns only the first screen on which we manipulate the presentation of prices. The cinema schedule as well as the second and third screen are identical across 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 first 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.

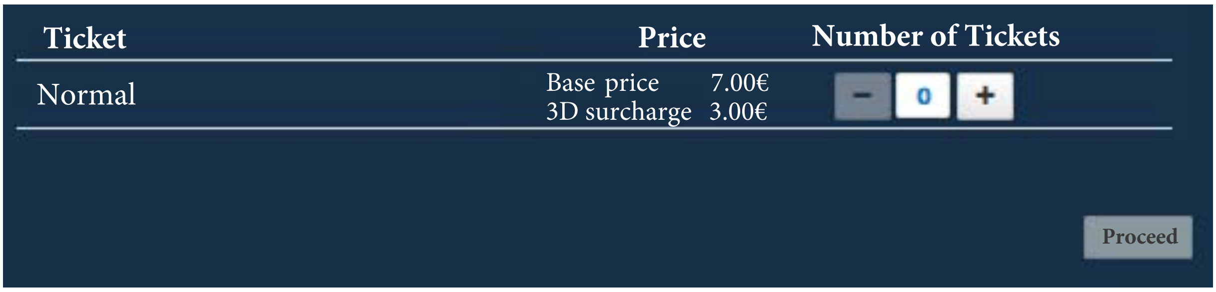
- **Inclusive**: In the first treatment, we present the overall ticket price, including the 3D surcharge, and add a footnote stating that the surcharge is already included (for an illustration see Figure 2 (a) and for the actual screen see Figure C.2 in the Appendix). This price presentation was also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

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



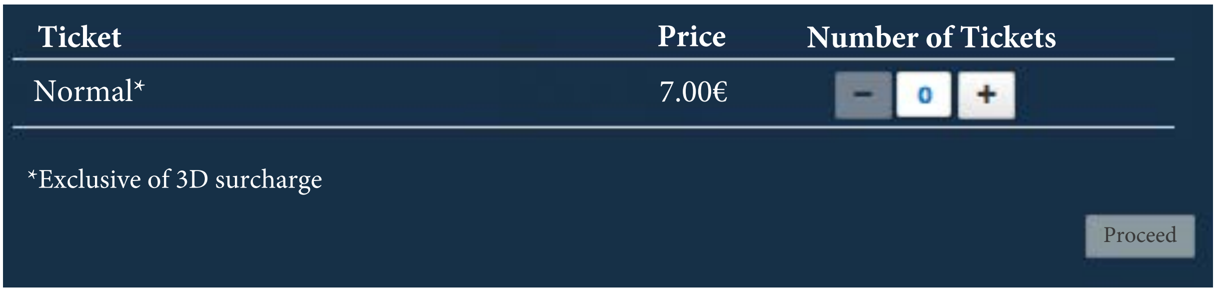
- **Partitioned**: In this treatment, we split up the full price by presenting the two price components – the base price and the 3D surcharge – in separate lines, but identical font and font size (see Figure 2 (b) and Figure C.3 in the Appendix).

Figure 2 (b). *Stylized design of the first 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 C.4 in the Appendix).[2]

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



[2] 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 certain, 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 no concern in our setup as surcharge-inclusive prices were used prior to our intervention.

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, a consumer sees the first screen of the purchase process (i.e., the price of a ticket as presented above) and chooses 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 to initiate a purchase process 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 to initiate a purchase process 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 second screen and since the purchase process is short and easy to cancel, we expect that the likelihood to complete a purchase process is independent of the price presentation. Also other types of cancellation costs (e.g., social image concerns or the attachment effect) are arguably negligible, so that consumers in *Partitioned* and *Shrouded* should be fully de-biased when observing the full price.

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

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 treatments randomly based on a unique user ID, so that our treatment effects are identified as accurately as in a laboratory setting. In a context where consumers tend to shop on a regular basis, a randomization at the cookie level as, for example, used in the study by Blake et al. (2018), might be problematic if consumers access the site with different devices or delete cookies regularly and are therefore reassigned to a different treatment.[3] Second, we

[3] 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). As an alternative to assigning treatments via cookies, one may think of treatment assignments that are based on IP

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 first screen) to her behavior outside of the frame (on the second and third screen). Third, we tracked the consumers' purchase history over the course of the experiment, so that we can also analyze long-term framing effects.

3. Empirical Analysis of Shopping Behavior

Data. Our intervention ran from April 24, 2017 until January 14, 2018. During this treatment period, we tracked all clicks in the cinema's online store at the level of an individual consumer, where each click refers to a different purchase process. We consider all 34,902 consumers who have clicked at least once on a 3D movie during our intervention, thereby being treated. We also analyze how the demand of these consumers for 2D movies was affected. Yet, we exclude other consumers who were only interested in 2D movies and never clicked on a 3D show.

Descriptives and randomization check. Table 1 provides an overview of the initiated and the completed purchases across the different treatments: in Panel A, we report the results conditional on the first click on a 3D movie during the treatment period, while in Panel B we aggregate all clicks over the 9 months of the intervention. Consistent with Hypothesis 1, the share of initiated purchase processes, both conditional on the first click and in the full sample, is smallest in *Inclusive*, at an intermediate level in *Partitioned*, and largest in *Shrouded*. In addition, we observe that the (unconditional) share of completed purchase processes does not very much across treatments, which is consistent with Hypothesis 2. This implies, in particular, that consumers in Shrouded are less likely to buy conditional on initiating a purchase process.

To test for our identifying assumption of random treatment allocation conditional on clicking on a 3D show for the first time, we performed several randomization checks. Using a X^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 click on a 3D show during our intervention (p-value = 1.000, X^2-test) or the 3D movie first clicked on (p-value = 0.933, X^2-test) into account, we cannot reject the null-hypothesis of random treatment allocation. This suggests that the randomization of treatments worked properly.

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 store with different IP addresses. Thus, we decided against both cookie- and IP-address-based randomizations.

Table 1. *Descriptive statistics for 3D movies across treatments.*

Panel A: First Click	Absolute Frequencies			Unconditional Relative Frequencies		
	Inclusive	Partitioned	Shrouded	Inclusive	Partitioned	Shrouded
Initiate purchase	5,285	5,391	5,969	45.67%	46.34%	51.03%
Complete purchase	3,931	3,853	3,943	33.97%	33.12%	33.71%
# Consumers in total	11,571	11,633	11,698	-	-	-
Panel B: All Clicks	Absolute Frequencies			Unconditional Relative Frequencies		
	Inclusive	Partitioned	Shrouded	Inclusive	Partitioned	Shrouded
Initiate purchase	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%
# Clicks in total	33,606	32,667	34,027	-	-	-

Empirical strategy. Our analysis is divided in two parts: First, we consider for each consumer only her first click on a 3D show during the treatment period. Second, we aggregate all clicks over the 9 months of our intervention, which allows us to test for long-term treatment effects.

Conditional on clicking on a 3D show for the first time, the treatment allocation is random (see the randomization checks above), so that the average treatment effects on the *unconditional* probability to initiate and to complete a purchase process for a 3D movie can be estimated using OLS. Importantly, we cannot identify the treatment effect on the probability to complete a purchase process conditional on initiating it, since the treatment might already affect initiations. Hence, conditional on initiating a purchase process, treatment allocation is not necessarily random. Our variables of interest thus are the unconditional share of initiated and completed purchase processes, whereby we drop the qualifier ‘’unconditional’’ in the following.

When aggregating all observations over the 9 months of our intervention period, it is important to keep in mind that, in principle, the estimates of the average treatment effects on the total number of initiated purchase processes might be biased due to differential attrition across treatments: the total number of clicks during the 9 months differs across treatments (see the last line of Table 1), which could be a systematic treatment effect and therefore potentially problematic. But, as we show in Appendix B.2, our naively estimated average treatment effects on the total number of initiated purchases are robust to imposing worst-case scenarios, in which we assume that all “missing” clicks due to differential attrition go against our hypotheses. If we analyze how our treatments affect the number of purchases over the 9 months, differential attrition is not an issue, but a crucial part of the potential treatment effects we are interested in.

Salience affects initiation, but not completion of purchases. Using for each consumer only her first click on a 3D show during the intervention period, we first find that shrouding the 3D surcharge significantly increases the probability that a consumer initiates the purchase process by 5.4 percentage points relative to a situation where the surcharge-inclusive price is presented right from the beginning (see Table 2). 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 probability to initiate a purchase process, which is inconsistent with Hypothesis 1.

As illustrated in Table 2, the estimated treatment effects are robust to adding several controls. The specification in the second column replicates 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) as well as for whether a 2D show of the same movie runs within +/- 1 hour in the same cinema. We estimate further specifictions in which we 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),[4] or an indicator of a blockbuster movie (fourth column),[5] or an indicator of weekends (fifth column). The estimated average treatment effects are stable across all specifications: relative to *Inclusive*, the average probability to initiate a purchase process for a 3D movie significantly increases by at least 5.2 percentage points in *Shrouded*, but does not differ significantly in *Partitioned*.

A second finding on the subsample of first clicks is that, consistent with Hypothesis 2, neither shrouding nor partitioning the 3D surcharge have a significant effect on the average probability to purchase tickets for a 3D movie. 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 second screen. The regression results are presented in Table 3, and the baseline treatment effects are again robust to the same set of controls. Also when using as the dependent variable an indicator of buying, at some point, tickets for the 3D show a consumer clicked on first during the treatment period, we find that neither partitioning nor shrouding has a significant effect on the average completion probability (see Table A.1 in the Appendix).

[4] Notice 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.

[5] 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 July, 18 2018).

Table 2. *Share of initiated purchase processes, conditional on the first click on a 3D show.*

Paramater	**Initiation**	**Initiation**	**Initiation**	**Initiation**	**Initiation**
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	-	-	-0.008	-	-
			(0.011)		
3D Sub x Partitioned	-	-	-0.004	-	-
			(0.014)		
3D Sub x Shrouded	-	-	-0.000	-	-
			(0.014)		
Blockbuster	-	-	-	0.158	-
				(0.134)	
Blockbuster x Partitioned	-	-	-	0.005	-
				(0.013)	
Blockbuster x Shrouded	-	-	-	-0.005	-
				(0.013)	
Weekend	-	-	-	-	0.000
					(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 to Table 2: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer initiates the purchase process for the 3D movie that she clicked on first during the treatment period. The independent variables of interest are treatment indicators (where 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), or an indicator of a blockbuster movie (fourth column), or an indicator of weekends (fifth column). Standard errors are provided in parentheses.*

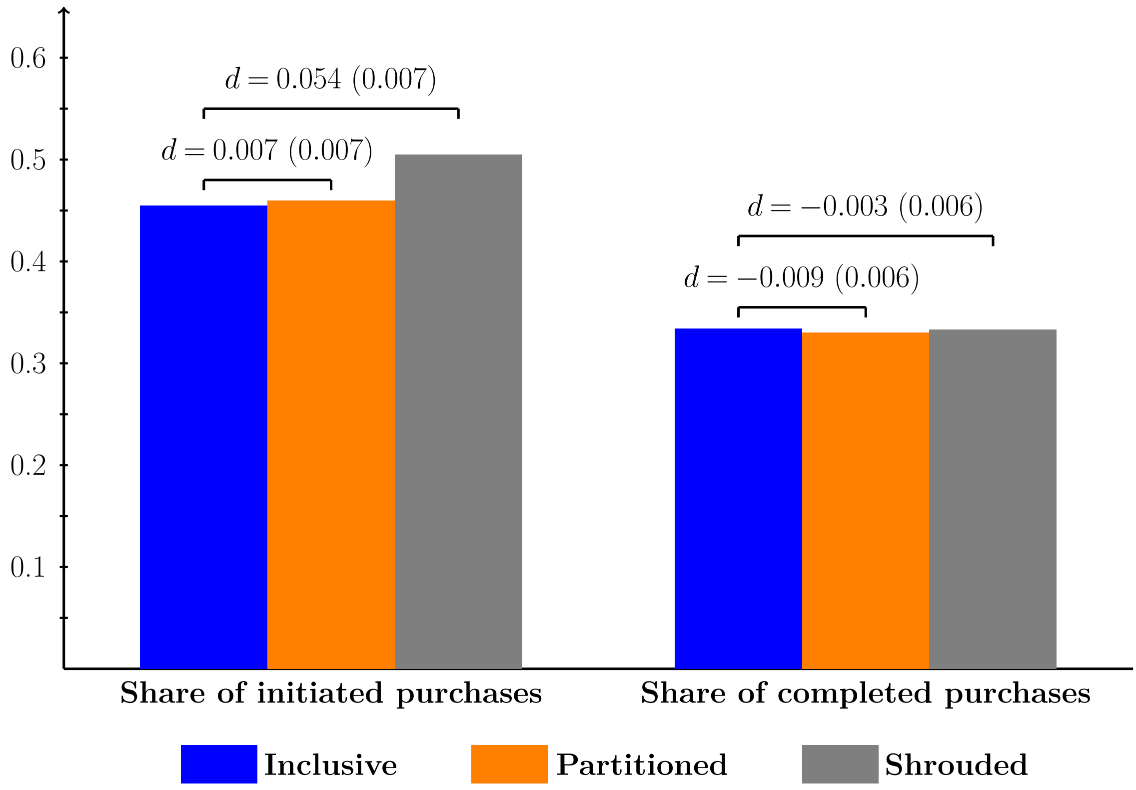
Table 3. *Share of completed purchase processes, conditional on the first click on a 3D show.*

Paramater	**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	-	-	-0.006	-	-
			(0.011)		
3D Sub x Partitioned	-	-	-0.010	-	-
			(0.013)		
3D Sub x Shrouded	-	-	-0.007	-	-
			(0.013)		
Blockbuster	-	-	-	0.297	-
				(0.127)	
Blockbuster x Partitioned	-	-	-	-0.004	-
				(0.013)	
Blockbuster x Shrouded	-	-	-	-0.005	-
				(0.013)	
Weekend	-	-	-	-	-0.001
					(0.013)
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 3: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer completes the purchase process for the 3D movie that she clicked on first during the treatment period. The independent variables of interest are treatment indicators (where 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), or an indicator of a blockbuster movie (fourth column), or an indicator of weekends (fifth column). Standard errors are provided in parentheses.*

In summary, when looking only at the subsample of first clicks, we find that the salience of the 3D surcharge affects the initiation, but not the completion of purchase processes for 3D movies. Figure 3 summarizes our findings on the subsample of first clicks.

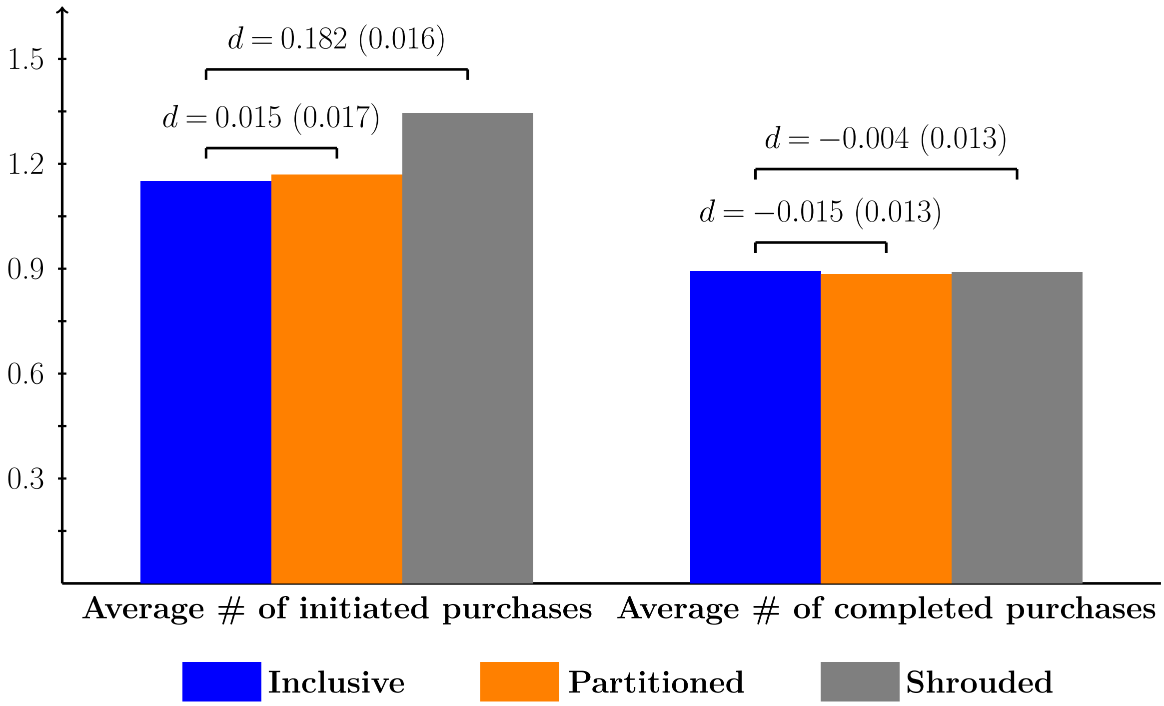
Figure 3. *Main findings on the subsample of first clicks.*



Notes to Figure 3: *The figure depicts the share of initiated and completed purchase processes, conditional on clicking on a 3D show for the first time, separately for the different treatments (Table 1). The estimated treatment effects refer to the first column of Table 2 (initiated purchases) and Table 3 (completed purchases), respectively.*

Our findings on the subsample of first clicks are robust to taking into account all observations over the 9 months of our intervention period. The average number of initiated purchase processes for 3D movies is significantly larger in *Shrouded* than it is in *Inclusive*, but not significantly different between *Partitioned* and *Inclusive* (see Table A.2 in the Appendix). Both findings are robust to imposing worst-case scenarios which assume that all "missing" clicks due to differential attrition in either treatment go against our hypotheses (see Appendix B.2). Moreover, we observe that the average number of completed purchases over the entire intervention period does not vary significantly across treatments (Table A.3 in the Appendix), which is again consistent with Hypothesis 2. These findings are summarized in Figure 4.

Figure 4. *Main findings on the full sample of all clicks.*



Notes to Figure 4: *The figure depicts the number of initiated and completed purchase processes in the different treatments (Table 1). The estimated treatment effects refer to the first column of Table A.2 (initiated purchases) and Table A.3 (completed purchases), respectively, in the Appendix. We provide standard errors in parentheses.*

Salience has no effect on repeat purchases. The panel structure of our data allows us to analyze whether shrouding or partitioning the 3D surcharge has adverse effects on the long-run 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-run 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 at least once tickets for a 3D movie (i.e., 22,405 out of 34,902 consumers) and 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 4, 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-run but also long-run demand for 3D movies is insensitive to the price presentation.

Table 4. *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 to Table 4: *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 (where 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. To address this problem, we look in more detail at the distribution of the number of purchases across treatments. Precisely, 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 treatment indicators. As depicted in Table 5, we do not find any significant treatment effect of shrouding the 3D surcharge on the average probability of buying at least k-times. When not contolling for multiple-hypotheses testing, partitioning the price into its two components has a weakly significant negative effect on the average probability of buying at least once tickets for a 3D movie (p-value = 0.081). In sum, the results presented in Table 5 confirm the previous observation that not only short-run but also long-run demand for 3D movies is insensitive to the price presentation.

Table 5. *Number of consumers who bought at least k-times tickets for a 3D movie.*

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 to Table 5: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer has bought 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.*

Revenues are unaffected by salience. So far, we have seen that our treatments have no effect on the average 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 A.4). Moreover, not only demand for 3D movies is insensitive to the presentation of prices, but also the demand for 2D movies does not vary significantly across treatments. This holds for both, the number of purchases as well as the number of purchased tickets for 2D movies (see Table A.5 in the Appendix). From that, we conclude that our treatments do not affect, at least for fixed prices, the cinema's revenues. Table 6 provides the corresponding regression results.

Table 6. *Average per-customer revenue.*

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 to Table 6: *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 9-month-intervention period. The independent variables are treatment indicators (where Inclusive serves as the base category). Standard errors are provided in parentheses.*

A simple back-on-the-envelope calculation shows that, with 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. On the Mechanism: Attention or Beliefs?

To shed light on the mechanism underlying our results, we discuss the role that wrong or missing beliefs about the size of the 3D surcharge could play in explaining the treatment effects on the probability to initiate a purchase process. In the following, we argue that these treatment effects are unlikely to be driven by the consumers' (wrong) beliefs about the 3D surcharge.

Wrong beliefs. The treatment effects on the likelihood to initiate a purchase process cannot be explained by wrong beliefs about the size of the 3D surcharge. To rationalize the increased likelihood to initiate a purchase process in *Shrouded* we would need to assume that, on average, consumers under-estimate the surcharge. If the consumers expect, on average, a surcharge of less than 3 Euro, then on the first screen of the purchase process for a 3D movie the corresponding 2D variant should more attractive, on average, in *Inclusive* than it is in *Partitioned*. But this implies that we should observe a (weakly) higher share of initiated purchase processes in *Inclusive* than in *Partitioned*, which is inconsistent with our findings.

Missing beliefs and learning. A non-attention-based explanantion of why consumers initiate more purchase processes for 3D movies in *Shrouded* than in *Inclusive* is that they are aware of the surcharge, but not of its size, and expect to learn the full price before confirming the purchase. If this is indeed the mechanism underlying our results, we would expect the treatment effects to become weaker with repeated visits of the online store, as consumers gain more experience with the surcharge. We thus estimate the average treatment effects on the likelihood to initiate a purchase process, conditional on a consumer's *second visit* of the online store.

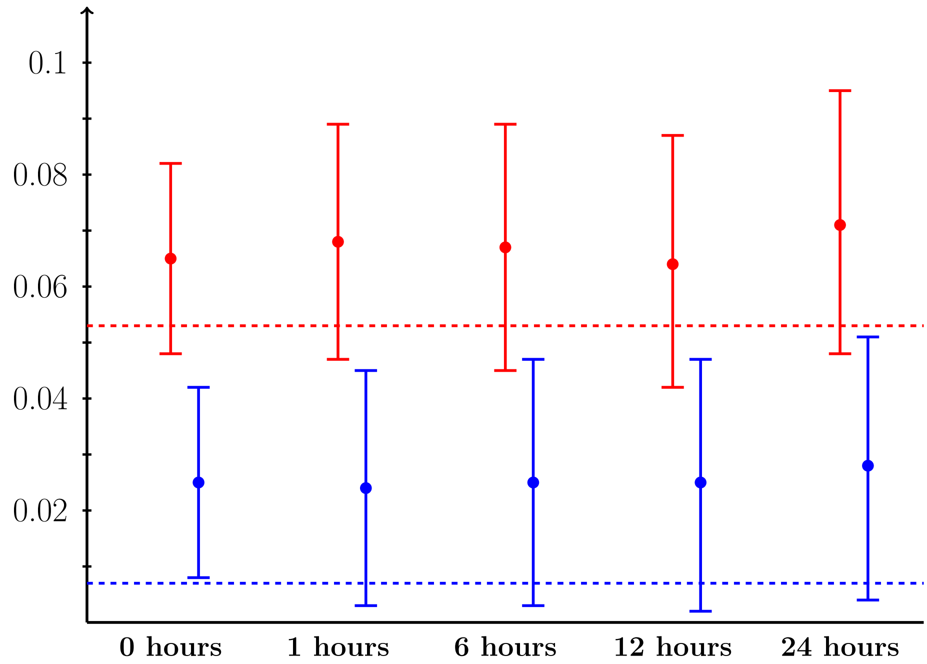
Since the definition of a consumer's second visit of the online store is somewhat ambiguous, we consider different specifications: we use for each consumer the first click on a 3D show that lies in the time interval starting exactly

- *0 hours* after her very first click on a 3D movie during the treatment period;
- *1 hour* after her very first click on a 3D movie during the treatment period;
- *6 hours* after her very first click on a 3D movie during the treatment period;
- *12 hours* after her very first click on a 3D movie during the treatment period;
- *24 hours* after her very first click on a 3D movie during the treatment period.

Importantly, when conditioning on a consumer's second visit of the online store, 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 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 visit of the online store is identical to that in the full sample (see Table A.8 in the Appendix).

As illustrated in Figure 5, conditional on the second visit, our treatments have a larger average effect on the probability to initiate a purchase process compared to the first visit. While, conditional on the first click on a 3D show, shrouding the surcharge increased the likelihood of initiating the purchase process by 5.3 p.p. on average (see the red dashed line in Figure 5), the average treatment effect conditional on the second visit ranges from 6.4 p.p. to 7.1 p.p. (see the red dots in Figure 5 and Table A.9 in the Appendix). Also the effect of partitioning the price into its two components becomes more pronounced. In contrast to our baseline results on the first visit of the online store, we now find a statistically significant positive effect of price partitioning (see the blue dots in Figure 5 together with the 95%-confidence intervals).[6]

Figure 5. *Treatment effects on the share of initiated purchases conditional on the second visit.*



Notes to Figure 5: *The figure depicts the estimated average treatment effects, together with 95%-cofidence intervals, on the probability to initiate a purchase process conditional on the second visit during the intervention period. We control for movie and time fixed effects as well as for whether a 2D substitute is available at broadly the same time. We consider different specifications of when the second session starts. The treatment effect of shrouding the 3D surcharge is depicted in red, while the effect of partitioning the price into its two components is depicted in blue. The dashed lines depict the estimated treatment effects conditional on the first click (see the second column of Table 2). The corresponding regression results are presented in Table A.9 in the Appendix.*

We interpret the finding that the treatment effects are not mitigated, but rather exarcerbated by additional experience with the online store, as evidence in favor of an attention-based explanation of our results. While we think of salience effects as unconscious distortions of perception that are unlikely to vanish with more experience, the effect of learning about the size of the surcharge by initiating the purchase process should be mitigated through experience.

[6] In the Appendix, we further verify that the estimated treatment effects conditional on the second visit are robust to imposing worst-case scenarios, in which all missing clicks due to differential attrition go against our hypotheses (see Table B.1 and B.2 in the Appendix).

Share of inattentive consumers. Given that our results are driven by inattention to the 3D surcharge, we can use the subsample of first clicks to estimate the share of inattentive consumers. Under the assumption that a consumer who initiates the purchase process in *Inclusive* would also initiate the process in *Shrouded*, we can estimate the following:

$$\frac{\text{Share of initiations in } Shrouded - \text{ Share of initiations in } Inclusive}{\text{Share of initiations in } Shrouded} = 10.50\%,$$

that is, more than 10% of the consumers who initiated the purchase process in *Shrouded* would not have done so in *Inclusive*, thereby revealing inattention to the shrouded surcharge. If we assume that inattention to shrouded surcharges is independent of the valuation for movie tickets and thus independent of the decision to initiate the purchase process in *Inclusive*, then 10.50% gives a point estimate of the overall share of inattentive consumers.

5. Related Literature

Now we put our results into perspective in comparison to the existing literature. We proceed in two steps. First, we discuss studies where the full price (including the surcharge) was presented only after the consumer confirmed the purchase. Second, we consider studies where the full price was presented before confirmation of the purchase, as it is the case in our experiment. While we consider only incentivized studies that are closely related to our setup (see Table 7), the survey of Greenleaf et al. (2016) also includes hypothetical studies.

Full price is not shown before purchase is confirmed. When the inclusive price is not presented prior to the purchase decision, a range of studies document positive effects of shrouding and price partitioning on demand or the willingness-to-pay. Price partitioning increases demand even though in some cases the inclusive price can be easily inferred from its components.

Three seminal studies that involve auctions are the lab experiment by Morwitz et al. (1998) as well as the field experiments by Hossain and Morgan (2006) and Brown et al. (2010), all of which find that shrouding of a surcharge increases bids significantly.[7] If the price is just partitioned – that is, the surcharge is made more salient than under shrouding –, consumers give significantly lower bids compared to the case where the surcharge is hidden in the product description (Brown et al., 2010). The results by Brown et al. (2010) are similar to our finding

[7] In Hossain and Morgan (2006), and Brown et al. (2010), for instance, all price components are presented, and in some treatments also in a salient manner, but the inclusive price summing up all price components is not shown.

that consumers are, on average, less likely to initiate a purchase process in *Partitioned* than in *Shrouded*. Comparisons of inclusive pricing with partitioned pricing (with a salient surcharge) yield mixed results (Morwitz et al., 1998; Xia and Monroe, 2004; Kim, 2006).

Taubinsky and Rees-Jones (2018) find in a controlled online shopping experiment that shrouding taxes, when displaying prices, increases demand on average. Similarly, making tolls non-salient by adopting an electronic toll collection system raises toll rates (Finkelstein, 2009).

Computational complexity could also affect whether different price frames affect demand. This is consistent with evidence suggesting that the demand effects of shrouding and price partitioning are more pronounced for multiplicative rather than additive surcharges, as the former result in a more complex optimization problem than the latter (Morwitz et al., 1998; Kim, 2006; Xia & Monroe, 2004; Kalaycı and Serra-Garcia, 2016).

To sum up, when the inclusive price is not presented prior to the purchase, consumers being inattentive to non-salient surcharges seems to be a reasonable explanation for why shrouding or partitioning a surcharge increases demand.[8]

Full price is shown before purchase is confirmed. Even if consumers are presented the surcharge-inclusive price before confirming the purchase, shrouding and partitioning in early stages of the purchase process can increase demand (Chetty et al., 2009; Feldman and Ruffle, 2015; Feldman et al., 2018; Blake et al., 2018). While inattention to non-salient surcharges by itself cannot account for this lack of de-biasing through presenting the full price, frictions that make it costly to cancel an initiated purchase process could. Frictions that may contribute to considerable cancellation costs in existing studies are the following:

1. *Social costs:* In physical stores, where cancellations are observed by other consumers or by a cashier, consumers might feel urged to stick to a social norm of not cancelling a purchase process. Moreover, a cancellation might be interpreted as an unpleasant signal of not being able to afford the products in the shopping basket.
2. *Attachment effect:* Initiating a purchase process attaches the consumer to the idea of buying the product, as a consequence of which a loss-averse consumer may refrain from cancelling. Relatedly, if attached to the idea of buying a product, a consumer

[8] Conversely, various field experiments have shown that making information salient can improve consumer choices. Englmaier et al. (2016) show that making flexible wages salient increases workers' effort provision, Tiefenbeck et al. (2016) show that making conservation gains salient reduces energy consumption, and Caflisch et al. (2018) show that making overdraft usage in banking salient reduces revenues earned through overdraft fees.

susceptible to confirmation bias[9] actively disregards non-salient information on surcharges that conflict with the intention to buy.

3. *Re-optimization costs:* Consumers might face costs of re-optimization, in particular, if they have to buy some version of the product (e.g., they have to book a flight to attend a conference). Re-optimization costs are arguably higher if surcharges are less transparent, in particular if unexpected price hikes cannot be easily attributed to single products (e.g., when buying a basket of different products for which it is unclear how much each product contributed to the unexpected price hike).
4. *Sunk-cost fallacy:* The sunk-cost fallacy – where sunk costs stem from time and effort devoted to the purchase process before the full price is presented – might prevent consumers from cancelling, even if actual re-optimization costs are neglible.

The lack of de-biasing in previous studies – which stands in contrast to our findings – can be explained by a difference in cancellation costs between the setups. Our setup minimizes the frictions above: cancellations are unobserved by other consumers which rules out social image concerns, the consumption value is rather low and the consequences of cancelling a purchase process are mild,[10] both of which limits the scope for the attachment effect, and finally the purchase process is very short and transparent, which limits both re-optimization costs and the sunk-cost fallacy. In previous studies, however, one or several frictions were present.

In a seminal field experiment, Chetty et al. (2009) find that displaying sales taxes on the price tags reduces demand for cosmetic and beauty products by 8%, meaning that tax-exclusive prices lead to higher revenues. While consumers learn the tax-inclusive price for their shopping basket at the cashier, social costs ("Others might think I cannot afford the items in my basket."), the sunk-costs fallacy ("I should buy, as it took so much time to fill the shopping basket.") or actual re-optimization costs may prevent cancellations.

Blake et al. (2018) find that, in an online shopping environment, shrouding of sales surcharges on tickets for shows and concerts increases the sales volume.[11] Due to the high consumption value of such a show or concert (arguably, much higher than for watching a

[9] Feldman and Ruffle (2015) denote this mechanism as the *confirmation bias theory of salience*.

[10] The next show of a given movie typically runs on the exact same day – often even at the same time – or the latest on the day after. Thus, even missing a particular show of a movie, in the case that it is sold out when looking for a movie the second time after having cancelled the purchase process the first time, does not affect the consumer's opportunity of watching the movie by much.

[11] Blake et al. (2018) also test how shrouding of surcharges affects the chosen quality. They document a quality upgrade effect whereby consumers substitute to a higher quality due to shrouding. By their model and their argumentation, such a quality upgrade effect should not play a role if the shrouded sum is additive as in our experiment. Unlike in the experiment by Blake et al. (2018) – where there is strong differentiation between seat categories – there is no vertical differentiation between products in our setting anyway.

movie), the attachment effect might drive their results.[12] In addition, the consequences of cancelling a purchase process are much more severe in their setting compared to ours: When cancelling the purchase of a concert ticket, for instance, a consumer risks not getting any tickets, in case she later changes her mind and the concert is already sold out. While a similar risk applies to a specific movie show, the crucial difference is that the next movie show runs on the same or the next day, while it is typically unclear when a given band will give the next concert in a city close by. Also the difference in the randomization techniques may contribute to the difference in results. If consumers are assigned to more than one treatment over time, as it may be the case in Blake et al. (2018), but not in our experiment, the true effect of shrouding a surcharge could be either mitigated or strengthened: Suppose, for instance, that a consumer is first assigned to a treatment with shrouded surcharges and afterwards to a treatment with a surcharge-inclusive price. This consumer, while being aware of the surcharge, might simply misinterpret the surcharge-inclusive price as an increase in the base price and therefore might buy less if the full price is presented right from the beginning (a critique that has been put forward, for instance, by Bernheim and Taubinsky, 2018). On the other hand, a consumer who saw the surcharge-inclusive price before being assigned to the treatment with shrouded surcharges might remember that a surcharge exists, thereby mitigating the true shrouding effect.

Feldman and Ruffle (2015) and Feldman et al. (2018) create a shopping environment in the lab and observe that initial shrouding (here, of sales taxes) increases demand for household items. Here, consumers buy a basket consisting of several products and, unlike in our setup, the purchase process cannot be cancelled, but the basket could just be re-optimized, which requires some time and effort. Since subjects in their experiments buy a basket of goods, it is also less transparent how much a single product contributes to an unexpected price hike.

In summary, all the studies discussed above have in common that for one or the other reason cancellation costs are non-neglible, which can explain why they observe demand effects that are absent in our experiment. Reassuringly, all studies that record also the cancellations of initiated purchase processes find that a considerable share of consumers cancel once the full price is presented; that is, also in other setups consumers are partially de-biased by presenting the full price prior to the purchase (see Column "If full price is presented" in Table 7).

[12] The attachment effect, as predicted by Kőszegi and Rabin (2006), is proportional to the consumption value net of the unexpected amount of the surcharge, which is for a multiplicative surcharge, as in Blake et al. (2018), proportional to the consumption value of the product. As pointed out by Feldman and Ruffle (2015), however, any loss-averse consumer who initiates a purchase process in an environment with a shrouded surcharge also overweights the unexpected surcharge once it is presented. Thus, when shrouding a surcharge for a product with a low consumption value, as in our setup, the attachment effect should not prevent cancellations at later stages.

Table 7. *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*
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, sunk-cost fallacy	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)

6. Conclusion

We present the results of a field experiment with more than 34,000 consumers of a German cinema that allows us to test for the effects of price salience on online shopping. We investigate 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 to initiate and to complete a purchase process.

We find that shrouding a 3D surcharge substantially increases the probability that a consumer initiates a purchase process for a 3D movie, compared to a presentation where the surcharge is included in the displayed price right from the beginning. This shrouding effect is sizeable, as we estimate that more than 10% of the consumers neglect the shrouded surcharge. 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 to complete a purchase process and therefore no effect on the cinema's profits.

We regard our results as an important complement to the existing empirical literature on salience effects, as we show that shrouding or partitioning surcharges alone can be inadequate instruments to trick consumers into buying more when it is not very costly to cancel an initiated purchase process. In this sense, our experimental findings provide a rationale for why many online shops (e.g., travel companies) make it time consuming to complete a purchase process after initiation, as this may increase perceived costs to cancel the purchase process.

To conclude, our results can also speak to regulators who are interested in how to improve consumer protection on the Internet. In particular, our findings lend support to policy measures that require firms to present the overall price right from the beginning or to keep cancellation costs as low as possible.[14] Such policies may help protect consumers with limited attention who might otherwise fall prey to price salience effects. These policy recommendations are independent of the exact mechanism that is underlying the observed shrouding effects. As long as the purchase process is initiated due to shrouded surcharges, cancellation costs may hinder the consumer from abandoning a purchase process and may therefore increase demand.

[14] The EU has followed several steps in this direction, in particular by tightening regulations on pricing strategies. For instance, 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." An overview of how firms' pricing strategies in general are regulated in the EU can be found, for instance, on https://europa.eu/youreurope/citizens/consumers/shopping/pricing-payments/index_en.htm.

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Appendix A: Additional Regression Analyses

A.1: Subsample of First Clicks

Table A.1. *Share of purchases for the 3D show clicked on first during the intervention.*

Paramater	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	-	-	0.004	-	-
			(0.012)		
3D Sub x Partitioned	-	-	-0.012	-	-
			(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	-	-	-	-	-0.004
					(0.014)
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 to Table A.1: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer buys, at some point, tickets for the 3D movie that she clicked on first during the treatment period. The independent variables of interest are treatment indicators (where 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), or an indicator of a blockbuster movie (fourth column), or an indicator of weekends (fifth column). Standard errors are provided in parentheses.*

A.2: Full Sample

In this subsection, we use all data over the 9-months-period of our intervention. First, we study the treatment effects on the average number of initiated purchase processes for 3D movies. In principle, we might be worried about selection effects due to differential attrition, but, as we argue in Appendix B.2, selection turns out not to be an issue. Second, we study the treatment effects on the average number of purchases and purchased tickets for 3D 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 tickets.

Initiated purchase processes. To address the question of whether the salience of prices affects the average number of initiated purchase processes for 3D movies over the period of our intervention, we regress the number of initiated purchase process on treatment indicators. The first column of Table A.2 presents the results underlying Figure 4, which is shown in the main text: while partitioning the price into its two components has no significant effect on the average number of initiated purchase processes for 3D movies, shrouding the 3D surcharge significantly increases the average number of initiated purchases by 0.182. To account for the data structure, we also estimate count models with the same result.[15] We present the results of a Negative binomial model with (in the second column) and without (in the third column) exposure.[16]

Table A.2. *Initiated purchase processes for 3D movies over the intervention period.*

Parameter	# Initiations	# Initiations	# Initiations
Partitioned	0.015	0.013	0.035
	(0.017)	(0.013)	(0.013)
Shrouded	0.182	0.146	0.138
	(0.016)	(0.009)	(0.012)
Model	OLS	NEGBIN	NEGBIN
Exposure	-	no	yes
# Observations	34,902	34,902	34,902

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

[15] For each of the three treatments, the conditional variance of the number of initiated purchase processes largely exceeds the conditional mean. Also in formal tests, 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 clicks on 3D shows.

Completed purchase processes. First, we regress the number of purchases for 3D movies on treatment indicators. The first column of Table A.3 presents the 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 A.4).

Table A.3. *Completed purchase processes 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 A.3: *Results of regressing the number of purchases for 3D movies on treatment indicators (where Inclusive serves as the base category), using OLS and Negative Binomial (NEGBIN) models with and without exposure. Standard errors are provided in parentheses.*

Table A.4. *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 A.4: *Results of regressing the number of purchased tickets for 3D movies on treatment indicators (where Inclusive serves as the base category), using OLS and Negative Binomial (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 purchases for 2D movies. As it is the case for 3D movies, we do neither find significant treatment effects on the number of purchases nor on the number of purchased tickets (see Table A.5).

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

A.3: Subsample of Second Clicks

Next, we ask whether our treatments affect the initiation and completion of the first purchase process in the second *visit* during our intervention period, as defined in Section 4. Table A.8 reports, for each of the specifications of the second visit, the distribution of consumers across treatments alongside the results of Fisher's exact tests with the null-hypotheses that the distribution over treatments is identical to that in the full sample.

Table A.8. *Number of consumers by treatments, conditional on the second session.*

	Inclusive	**Partitioned**	**Shrouded**	**Total**	**p-value**
All	11,571	11,633	11,698	34,902	-
0 hours	6,564	6,589	6,750	19,903	0.637
1 hour	4,152	4,135	4,213	12,500	0.869
6 hours	3,709	3,663	3,752	11,124	0.736
12 hours	3,599	3,542	3,614	10,755	0.724
24 hours	3,367	3,300	3,397	10,064	0.596

Notes to Table A.8: *The last column presents the p-value of a Fisher's exact test with null-hypothesis that the distribution over treatments in the respective subsample is the same as in the full sample.*

Given that selection does not seem to be an issue, we estimate average treatment effects on the probability to initiate a purchase process using OLS (Table A.9). We find that, conditional on the first click in the second session, salience effects become stronger: relative to *Inclusive*, the average probability to initiate a purchase process significantly increases by around 2.5 p.p. in *Partitioned* (p-value < 0.05) and by more than 6.4 p.p. in *Shrouded* (p-value < 0.001).

Table A.9. *Initiation of purchase processes for 3D movies, conditional on second session.*

Paramater	**0 hours**	**1 hour**	**6 hours**	**12 hours**	**24 hours**
Partitioned	0.025	0.024	0.025	0.025	0.028
	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)
Shrouded	0.065	0.068	0.067	0.064	0.071
	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)
Movie FE	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes
2D Substitute Dummy	yes	yes	yes	yes	yes
# Observations	19,903	12,500	11,124	10,755	10,064

Notes to Table A.9: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer initiates the purchase process for the 3D movie that she clicked on first during the second session. The independent variables of interest are treatment indicators (where Inclusive serves as the base category). We add movie and time fixed effects, and a control for whether a 2D substitute is available at the same cinema at broadly the same time. Standard errors are provided in parentheses.*

Interestingly, while *Partitioned* does not have a significant effect on the average probability to initiate a purchase process conditional on the first click on a 3D movie (see Table 2 in the main text), it does have a significant effect conditional on the first click in the second session. Also the effect of shrouding the 3D surcharge becomes more pronounced in the second session. Although selection does not seem to be a problem here, we will, in Appendix B.1, consider worst-case scenarios to obtain lower bounds on the estimated treatment effects.

While the treatment effects on the probability to initiate a purchase process become more pronounced in the second session, the treatment effects on the probability to complete a purchase process do not change: as for the subsample of first clicks, neither partitioning the total price into its two components nor shrouding the 3D surcharge has a significant effect on average probability to buy tickets (see Table A.10).

Table A.10. *Completion of purchase processes for 3D movies, conditional on second session.*

Paramater	**0 hours**	**1 hour**	**6 hours**	**12 hours**	**24 hours**
Partitioned	0.008	0.008	0.003	0.003	0.005
	(0.008)	(0.010)	(0.011)	(0.011)	(0.011)
Shrouded	0.003	0.005	-0.006	-0.006	-0.002
	(0.008)	(0.010)	(0.011)	(0.011)	(0.011)
Movie FE	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes
2D Substitute Dummy	yes	yes	yes	yes	yes
# Observations	19,903	12,500	11,124	10,755	10,064

Notes to Table A.10: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer completes the purchase process for the 3D movie that she clicked on first during the second session. The independent variables of interest are treatment indicators (where Inclusive serves as the base category). We add movie and time fixed effects, and a control for whether a 2D substitute is available at the same cinema at broadly the same time. Standard errors are provided in parentheses.*

Appendix B: Selection Issues and Worst-Case Scenarios

B.1: Worst-Case Scenarios for the Treatment Effects in the Second Session

To begin with, we consider the effect of partitioning the total price into its two components on the average probability to initiate a purchase process. To obtain lower bounds on the estimated treatment effects in Table A.9, 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 initiate the purchase process until the number of consumers is the same as in *Partitioned*. That is indeed the case for the specifications *1 hour* (17 consumers), *6 hours* (46 consumers), *12 hours* (57 consumers), and *24 hours* (67 consumers). If there are more consumers in *Partitioned*, then we randomly drop consumers from *Partitioned* who initiated the purchase process until the number of consumers is the same as in *Inclusive*. That is indeed the case for *0 hour* (25 consumers).

We observe that for all five specifications the treatment effects have roughly the same size as before. While the effects for *0 hours* and for *1 hour* are still significantly different from zero at a p-value < 0.05, the treatment effects for the remaining specifications are significant only at a p-value < 0.10 (see Table B.1). In summary, the estimated treatment effects of partitioning the total price, conditional on the second session, are robust to imposing a worst-case scenario.

Table B.1. *Worst-case scenario for Inclusive vs. Partitioned, conditional on second session.*

Paramater	**0 hours**	**1 hour**	**6 hours**	**12 hours**	**24 hours**
Partitioned	0.023	0.023	0.020	0.019	0.020
	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)
Movie FE	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes
2D Substitute Dummy	yes	yes	yes	yes	yes
# Observations	13,128	8,270	7,326	7,084	6,600

Notes to Table B.1: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer initiates the purchase process for the 3D movie that she clicked on first during the second session. The independent variables of interest is treatment indicator for Partitioned. We add movie and time fixed effects, and a control for whether a 2D substitute is available at the same cinema at broadly the same time. Standard errors are provided in parentheses.*

Next, we consider the effect of shrouding the 3D surcharge on the average probability to initiate a purchase process. To obtain lower bounds on the estimated treatment effects in Table A.9, we equalize the number of consumers across treatments in the same way as above: in all five specifications there are more consumers in *Shrouded* than in *Inclusive*, namely, 186 consumers for *0 hour*, 61 consumers for *1 hour*, 43 consumers for *6 hours*, 15 consumers *12 hours*, and 30 consumers for *24 hours*, which we drop to equalize the number of consumers.

We observe that for all five specifications the treatment effects have roughly the same size as before. Moreover, for any of the specifications, the estimated treatment effect remains significantly different from zero at a p-value < 0.001 (see Table B.2). In summary, the estimated treatment effects of shrouding the 3D surcharge, conditional on the second session, are robust to imposing a worst-case scenario.

Table B.2. *Worst-case scenario for Inclusive vs. Shrouded, conditional on second session.*

Paramater	**0 hours**	**1 hour**	**6 hours**	**12 hours**	**24 hours**
Shrouded	0.053	0.062	0.062	0.062	0.066
	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)
Movie FE	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes
2D Substitute Dummy	yes	yes	yes	yes	yes
# Observations	13,128	8,304	7,418	7,198	6,734

Notes to Table B.1: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer initiates the purchase process for the 3D movie that she clicked on first during the second session. The independent variables of interest is treatment indicator for Shrouded. We add movie and time fixed effects, and a control for whether a 2D substitute is available at the same cinema at broadly the same time. Standard errors are provided in parentheses.*

B.2: Worst-Case Scenarios for the Treatment Effects on the Full Sample

To address potential selection issues and to assess the validity of the treatment effects on the average number of initiated purchase processes over the 9 months of our intervention, as presented in Table A.4, we again impose worst-case scenarios.

First, we consider the effect of partitioning the total price into its two components. For that, we assume that all ”missing” clicks in *Partitioned* go against Hypothesis 1. Over the 9 months of our intervention, consumers in *Partitioned* have 939 fewer clicks on 3D shows than consumers in *Inclusive.* The most conservative way to test for the average treatment effect of price partitioning on the number of initiated purchase processes is to assume that *all* missing clicks in *Partitioned* would have been drop-outs on the first screen. Then we add these missing drop-outs to those consumers with the highest rates of initiated purchase processes and the smallest numbers of clicks on 3D movies[18], as this maximizes the decrease in the average initiation rate.[19] Given these assumptions, we estimate an OLS regression as well as Negative Binomial models – with and without exposure – with the accordingly adjusted number of initiated purchase processes as the dependent variable and an indicator of *Partitioned* as the independent variable to obtain a lower bound on the average treatment effect (see Table B.3).

Table B.3. *Lower-bound estimation of initiations in Partitioned (worst-case scenario).*

Parameter	**# Initiations**	**# Initiations**	**# Initiations**
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.3: *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 Negative Binomial (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 the number of initiated purchase processes, but also that it does not decrease the average number of initiated purchase processes, which would have been the exact opposite of Hypothesis 1.

Second, we consider the effect of shrouding the 3D surcharge in more detail. Over the 9 months of our intervention, the consumers in *Shrouded* have 421 more clicks on 3D shows than consumers in *Inclusive*. In order to obtain a lower bound on the average treatment effect of shrouding on the number of initiated purchase processes, we assume that consumers in *Inclusive* had 421 more clicks on 3D shows with no additional drop-outs on the first screen. The most conservative way to allocate these "missing" clicks in *Inclusive* is to add them to those consumers with the lowest initiation rates and the smallest numbers of clicks on 3D movies[20],

[18] There are more than 939 consumers in *Partitioned* with only a single click on a 3D movie and no drop-out on the initial screen (i.e., they initiated the purchase process). Among these consumers, we chose randomly and increased both the number of clicks on 3D movies and the corresponding number of drop-outs on the initial screen by one to end up with the adjusted number of clicks and drop-outs, respectively, that we use to estimate a lower bound on the average treatment effect on the number of initiated purchase processes.

[19] For illustrative purposes, denote as D_i the number of drop-outs and as N_i the number of clicks on 3D movies by consumer i. In addition, let $s_i := (N_i - D_i)/N_i$ be her initiation rate. Now, increasing both D_i and N_i by one results in a decrease of the initiation 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 click on a 3D movie and one drop-out on the initial screen. Among these consumers, we chose randomly and increased the number of clicks on 3D movies by one to end up with the adjusted number of clicks that we use to estimate a lower bound on the ATE.

as this maximizes the increase in the average initiation rate.[21] Given these assumptions, we estimate an OLS regression as well as Negative Binomial models – with and without exposure – with the accordingly adjusted number of initiated purchase processes as the dependent variable and an indicator of *Shrouded* as the independent variable to obtain a lower bound on the average treatment effect (see Table B.4). As it is the case for *Partitioned,* also for *Shrouded* the worst-case scenario confirms the naive estimates in Table A.4, both qualitatively and quantitatively: the average number of initiated purchase processes is significantly larger in *Shrouded* than in *Inclusive*, and the estimated treatment effect is of economically relevant size.

Table B.4. *Lower-bound estimation of initiations in Shrouded (worst-case scenario).*

Parameter	**# Initiations**	**# Initiations**	**# Initiations**
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.3: *Results of worst-case scenario in which we regress the adjusted number of initiated purchase processes for 3D movies on an indicator for Shrouded, using OLS and Negative Binomial (NEGBIN) models with and without exposure. Standard errors are provided in parentheses.*

[21] Using the notation from above, we conclude that increasing the number of clicks on 3D movies, N_i, by one increases the initiation rate by $(1 - s_i)/(N_i + 1)$, which decreases in s_i and in N_i.

Appendix C: Decision Screens in the Different Treatments

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

Solo: A Star Wars Story 3D

FSK 12 · 135 Min.

Nach seinem Rausschmiss aus der Flugakademie wird Han Solo von dem zwielichtigen Gangster Tobias Beck auf eine gefährliche Mission geschickt.

Mi 20.06	Do 21.06	Fr 22.06	Sa 23.06	So 24.06	Mo 25.06	Di 26.06
14:30	16:30	16:30	16:30	16:30	16:30	16:30
16:50	23:00	19:40	19:40	19:40	19:40	19:40
22:20		23:00	23:00	23:00	23:00	23:00

Spielzeiten der kommenden Woche ab Dienstag

Solo: A Star Wars Story

FSK 12 · 135 Min.

Nach seinem Rausschmiss aus der Flugakademie wird Han Solo von dem zwielichtigen Gangster Tobias Beck auf eine gefährliche Mission geschickt.

Cinedom Premium Black Box in Dolby Atmos

Mi 20.06	Do 21.06	Fr 22.06	Sa 23.06	So 24.06	Mo 25.06	Di 26.06
17:00	-	-	-	-	-	-

Mi 20.06	Do 21.06	Fr 22.06	Sa 23.06	So 24.06	Mo 25.06	Di 26.06
20:10	14:00	14:00	12:10	12:10	14:00	14:00
22:40	16:30	16:30	14:00	14:00	16:30	16:30
	19:30	19:30	16:30	16:30	19:30	19:30
	22:20	22:20	19:30	19:30	22:20	22:20
			22:20	23:00		

Spielzeiten der kommenden Woche ab Dienstag

Notes to Figure C.1: *Before clicking on a given show (i.e., a combination 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 C.2. *Price presentation on the initial screen in Inclusive.*

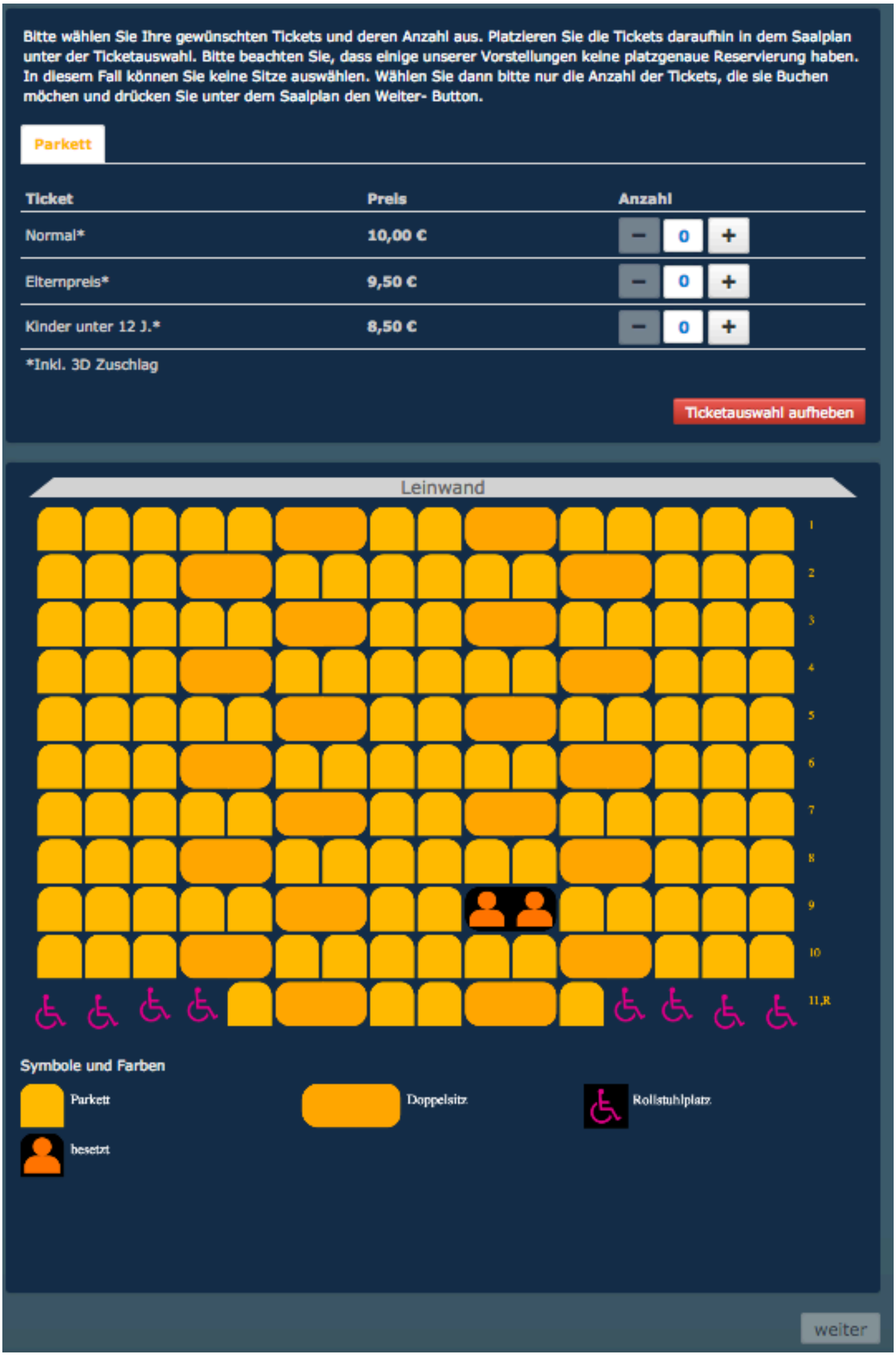


Figure C.3. *Price presentation on the initial screen in Partitioned.*

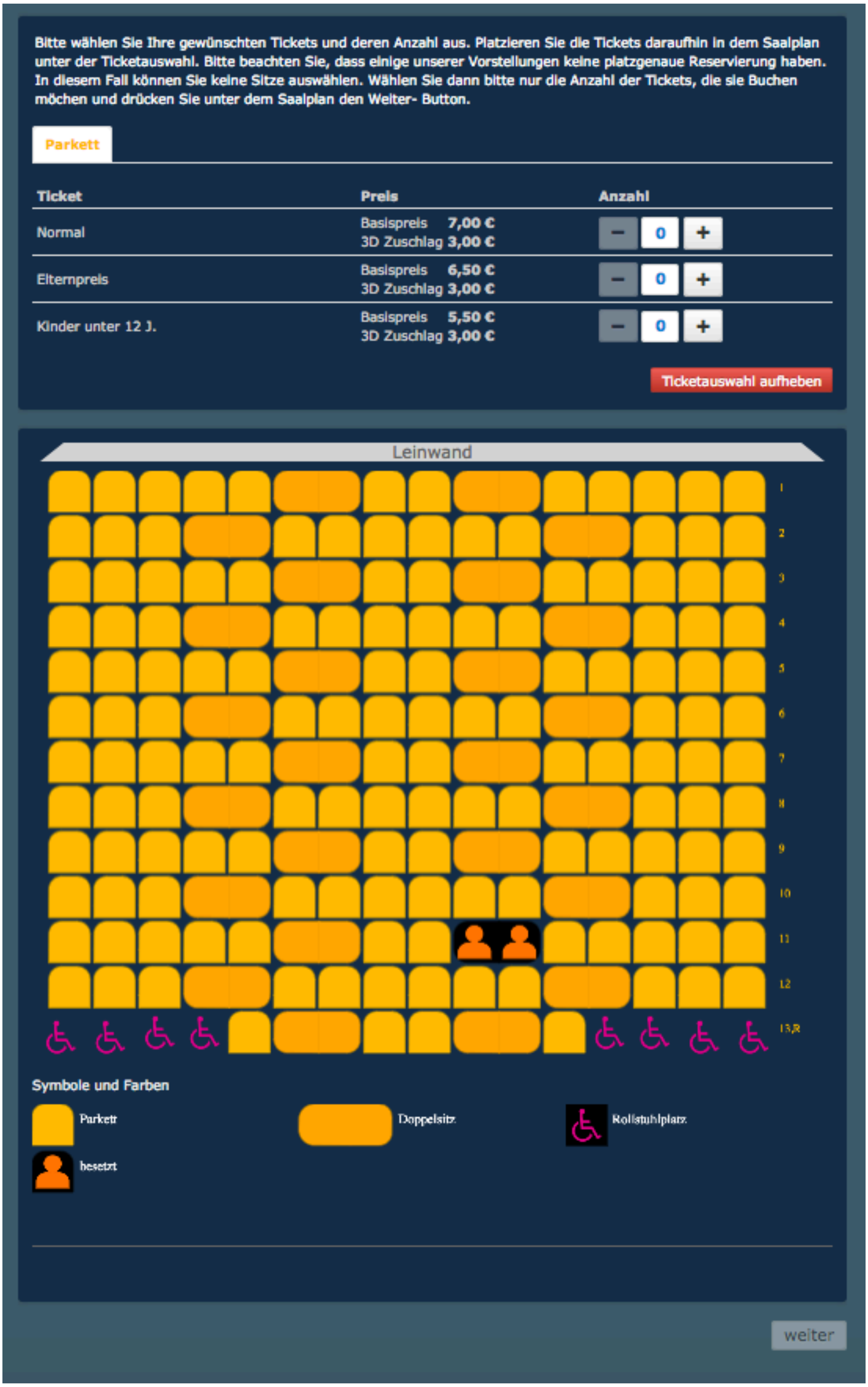
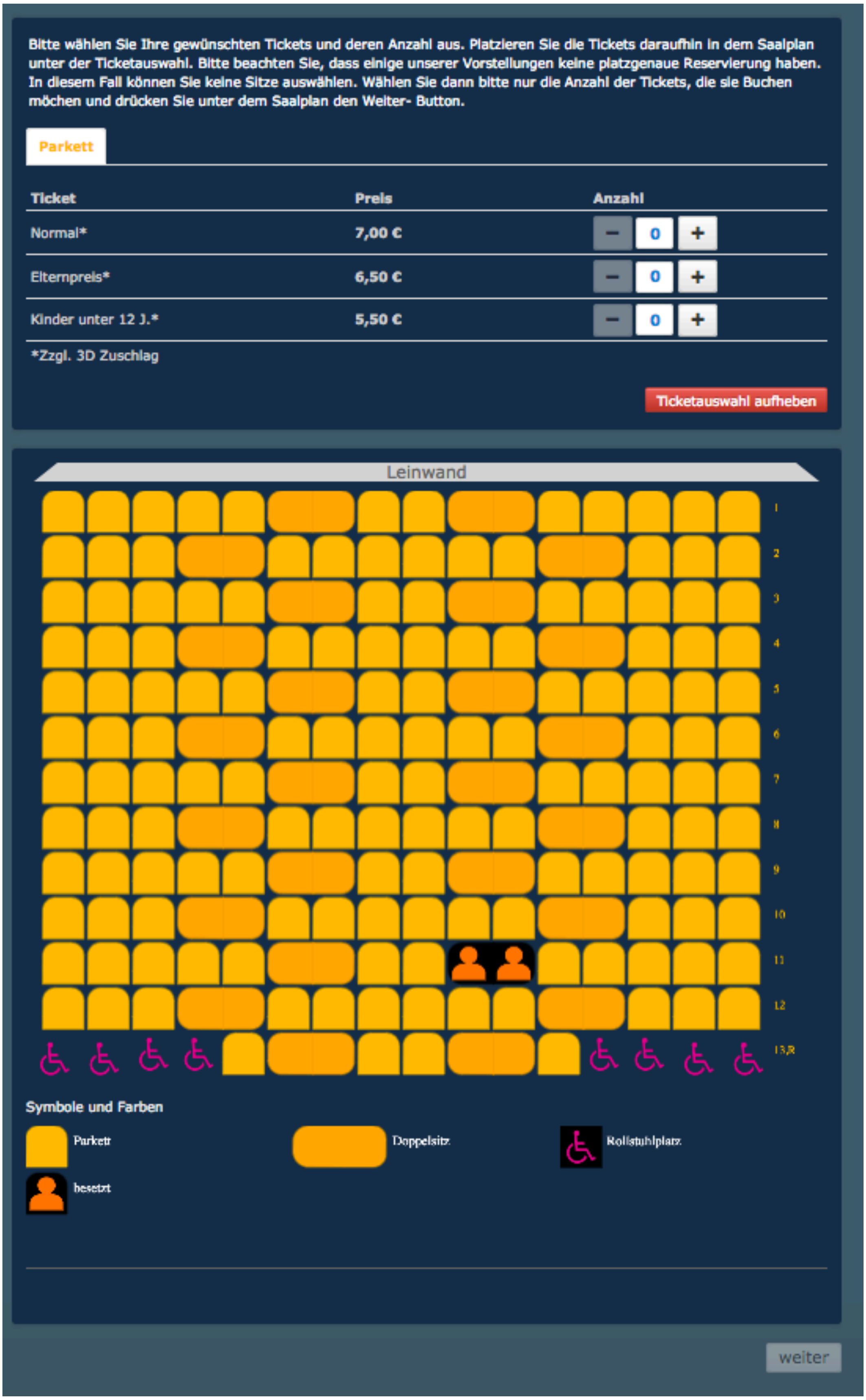


Figure C.4. *Price presentation on the initial screen in Exclusive.*



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