

Kairies-Schwarz, Nadja; Harrison, Glenn W.; Han, Johann

Conference Paper

Deductibles and Health Care Utilization: An Experiment on the Role of Forward-Looking Behavior

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2018: Digitale Wirtschaft - Session: Applied Behavioral Models II, No. B08-V2

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Kairies-Schwarz, Nadja; Harrison, Glenn W.; Han, Johann (2018) : Deductibles and Health Care Utilization: An Experiment on the Role of Forward-Looking Behavior, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2018: Digitale Wirtschaft - Session: Applied Behavioral Models II, No. B08-V2, ZBW - Leibniz-Informationszentrum Wirtschaft, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/181588>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Deductibles and Health Care Utilization: An Experiment on the Role of Forward-Looking Behavior

Johann Han, Glenn W. Harrison, Nadja Kairies-Schwarz^{*†}

- *Preliminary Version* -

Abstract

Recent evidence on nonlinear insurance contracts finds that individuals react to the embedded dynamic incentives by changing health care utilization. However, with field data it is difficult to keep the spot price among individuals constant while systematically varying the future price. To do so, we use a controlled laboratory experiment in which subjects are insured by a health plan with a deductible and go through a cycle of periods. In each period they face probabilistic health events and have to choose whether to seek treatment or not. We vary the likelihood of hitting the deductible by varying the number of periods and the height of the deductible, as well as controlling whether subjects receive regular information updates on their remaining deductible. We also elicit individual risk and time preferences. Our results show that varying the future price has a significant effect on spending behavior, regardless of whether the same future price is reached by changing the deductible or the number of periods. At an individual level, we identify perfectly forward-looking as well as perfectly myopic individuals. We find that a relationship between spending on health care and risk preferences, forward-looking behavior and giving information on the height of the deductible.

JEL classification: I13; C91.

Keywords: Health insurance, nonlinear prices, forward-looking behavior, laboratory experiment, risk and time preferences.

^{*} University of Duisburg-Essen, Faculty of Economics and Business Administration & CINCH – National Health Economics Research Center, Berliner Platz 6-8, 45127 Essen, Germany; email: johann.han@uni-due.de, nadja.kairies@ibes.uni-due.de (corresponding author).

[†] We thank Daniel Avdic, Friedrich Breyer, Simon Decker, Ben Handel, Matthias Kifmann, Jimmy Martinez Correa, Christian Waibel, as well as participants at the dggö Jahrestagung 2017 in Basel, Young Economists Meeting in Brno, HESG Meeting in Aberdeen, 4th EuHEA PhD conference in Lausanne, dggö workshop on “Allocation and Distribution” in Hamburg, and the 5th Workshop in Behavioral and Experimental Health Economics in Atlanta. Financial support provided by the Deutsche Forschungsgemeinschaft (German Research Foundation FOR-655) and the Bundesministerium für Bildung und Forschung (Federal Ministry of Education and Research) is gratefully acknowledged.

1. Introduction

In an effort to reduce health care spending, policy makers, health insurance companies, and employers have tried to incentivize the demand side by incorporating some form of cost sharing in their policies. One popular way to do this is to include deductibles in health care plans. Such deductible plans affect health care prices over time in the sense that an individual will pay higher prices for the same health service before than after having reached the deductible.

How health insurance pricing affects consumers' medical spending has been actively studied with field data. The first major contribution was the RAND Health Insurance Experiment (Keeler and Rolph, 1988; Aron-Dine et al. 2013), followed by the Oregon Health Insurance Experiment (Finkelstein et al., 2012). Given the nonlinear pricing structure over time in deductible plans, it is critical to investigate whether consumers react to other prices than the spot price. More recent studies have therefore studied the effects of nonlinear contracts on utilization behavior either using firm or claim level data for health insurance plans (Cardon and Hendel, 2001; Kowalski, 2015; Aron-Dine et al., 2015; or Brot-Goldberg et al., 2017), or data for Medicare Part D plans (Einav et al., 2015; Dalton et al., 2017; or Abaluck et al., 2015).¹

To investigate the effect of dynamic incentives created by deductible plans on health care utilization behavior, one would ideally keep the spot price constant while generating variation in the future price. Aron-Dine et al. (2015), for instance, use an empirical strategy that compares individuals who join the same deductible health plans at different times of the year. These individuals face the same spot price but different future prices due to variations in the remaining time until the end of the year where the deductible resets. By using claim-level data from employer-provided health insurance in the U.S., Aron-Dine et al. (2015) are able to show that consumers react to more than just the spot price. Initial health care utilization is higher for individuals who joined early in the year and thus face a low future price. However, their approach strongly depends on the fact that reasons for joining in different months be viewed exogenous to health care utilization behavior.

Irrespective of the empirical strategy, each of these studies investigating the effects of nonlinear contracts on utilization behavior face potential confounders, which make it difficult to manipulate the future price while holding the spot price constant. While seasonality might be relatively easy to account for, liquidity constraints, intertemporal substitution and comorbidities might substantially affect utilization and are difficult to control for in the field.

We complement the empirical work on the effects of nonlinear deductible contracts on health utilization behavior by using a controlled laboratory experiment. Compared to the field, the laboratory allows one to perfectly control for a constant spot price while varying the future price, as well as for

¹ Earlier theoretical contributions addressing the issue include Keeler et al (1977) and Ellis (1986).

other confounding factors. In the experiment subjects go through a cycle of periods and are insured by a health plan with a deductible. In each period they face probabilistic health events and have to choose between seeking treatment or not. We also elicit individual risk and time preferences for each subject in separate tasks, similar to Andersen et al. (2008).

We investigate other factors that might influence health care utilization in the context of dynamic incentives. First, we manipulate the channel through which the same future price is generated. To do this, we either vary the contract duration length or the deductible height. Second, we vary whether subjects receive regular information updates on their accumulated costs and remaining deductible. This information may be relevant in the context of healthcare utilization since health insurance plans with deductibles are complex, and evidence shows that many individuals do not completely understand them. For instance, Lowenstein et al. (2013) report that in a survey only 14% of individuals in the sample answered four multiple choice questions on the four basic components of health plans (deductibles, copayments, coinsurance and maximum out of pocket costs) correctly. Not understanding their health insurance plans implies that individuals are unlikely to respond to the incentives. One way to improve understanding of health care plans and thus health care utilization is to provide individuals with better information about their health plans, or simplify the decision process. Evidence from various field experiments shows that providing individuals with information, or simplifying the decision process, can indeed lead to better decision outcomes; see Kling et al. (2012) for Medicare Part D plan choices, Hastings et al. (2008) for low income families choosing schools with high test scores, or Bhargava and Manoli (2015) for economically and socially disadvantaged families to claiming eligible tax benefits.

In line with the empirical evidence investigating the effects of nonlinear contracts on health utilization behavior, we find that individuals respond to the dynamic incentives created by deductible plans. Our results show that the future price has a significant effect on spending behavior. The channel by which the future price is manipulated, whether the same future price is reached by changing the deductible or the number of periods, seems to be secondary. At the individual level we find perfectly forward-looking as well as perfectly myopic individuals. Moreover, we find a relationship between spending on health care and risk preferences, forward-looking behavior and giving information on the height of the deductible.

In Section 2 we lay out the experimental design and procedure. In Section 3 we report our results before presenting conclusions in Section 4.

2. Experimental Design

2.1 Decision Situation

We employed a laboratory experiment with a sequential design. In the first part we elicited individual risk and time preferences similar to Andersen et al. (2008). In the second part we analyzed health utilization behavior under dynamic incentives.²

In the first part of the experiment, risk and time preferences were elicited, following Andersen et al. (2008) where subjects made decisions in separate multiple price lists. The tasks that revealed risk preferences were designed after Holt and Laury (2002). Subjects had to make choices between lotteries that differed in terms of riskiness. In the time preferences part subjects had to choose between an early payment (after one week) and a late payment (after 5 weeks).³ Overall, each subject made 20 decisions to identify risk preferences and 10 decisions for the identification of time preferences.

Preferences were elicited in this way for every subject participating in the experiment. Decisions for risk and time preferences were not presented with a health frame as they were in a separate part. Thus, inconsistencies between parts might derive from a more complex decision scenario in the health utilization part or from preferences that are specific to a health frame. Although we cannot disentangle these motives, we try to control for complexity by varying the availability of information about the remaining deductible and thereby decrease the cognitive burden.

In the second part of the experiment, we investigated subjects' health care utilization behavior given dynamic incentives. This part varied between treatments as shown in Table 3. The general design was inspired by a dynamic model outlined in Aron-Dine et al. (2012) and is also similar to Einav et al. (2015) in the Medicare D prescription drug context. In a periodic game, subjects went through a cycle of decision situations. Each period a subject received an income of 50 ECU (experimental currency unit)⁴ and faced one of three possible events: (a) Healthy, (b) Sickness A or (c) Sickness B. The health events were drawn from a probability distribution known to all participants. Realization 'Healthy' could occur with a probability of 0.6 while 'Sickness A' and 'Sickness B' could each happen with probability of 0.2 as shown in Table 1.

² We used this order because we did not want income effects from the utilization part to affect the elicitation of preferences. Since the payments for the elicitation part were randomly determined after the whole experiment was concluded, this concern did not arise with the given order. We controlled for potential order effects by reversing the order of both parts in one treatment.

³ Here, we varied from Andersen et al. (2008) who had more variation in time horizons and used a constant "principal" in the shorter horizon. We go with a simplified setting closer to the replication by Andreoni et al. (2015).

⁴ The conversion rate was 1 ECU = 0.015 EUR.

Table 1: Potential Health States, Costs of (Not) Treating, and Event Probabilities

Health state	Treatment cost	Opportunity cost without treatment	Probability of event
Healthy	0	0	0.6
Sickness A	50	50	0.2
Sickness B	50	30	0.2

If a subject was healthy, they did not face any costs, did not make any decision and kept the periodic income. If a subject was sick, they had to decide whether to get treated or not. While costs for both decisions did not differ for Sickness A, it was cheaper to leave the sickness untreated with Sickness B. Given the periodic income, subjects were always able to afford any decision they made. There were no consequences of the decision on future health outcomes or probabilities and subjects knew that. Depending on the treatment, subjects went through 52 or 26 decision periods. The order of health events was drawn prior to the experiment and was the same between all treatments at least until the 26th period, since some sessions ended after that (see Table 2). This way we could control for “seasonality” that could occur in the field, where locally or temporarily concentrated health events could affect utilization behavior.

Table 2: Draw of Health Events for Every Period

Period	1	2	3	4	5	6	7	8	9	10	11	12	13
Health	G	B	G	G	A	G	G	B	G	G	A	G	A
Period	14	15	16	17	18	19	20	21	22	23	24	25	26
Health	G	B	G	B	B	G	G	G	B	G	G	G	A
Period	27	28	29	30	31	32	33	34	35	36	37	38	39
Health	B	G	G	B	A	A	G	B	G	G	B	B	G
Period	40	41	42	43	44	45	46	47	48	49	50	51	52
Health	A	G	G	A	G	G	G	B	G	G	B	G	A

Note: G = good health; A = Sickness A; B = Sickness B. Order of health events was drawn before the experiments and was identical for all sessions and treatments.

Apart from receiving the periodic income, subjects were told that they had insurance coverage for negative health events after they had incurred medical spending beyond a deductible. The deductible height varied depending on the experimental treatment. If subjects decided to treat a sickness, their spending was deducted from the deductible. Medical spending beyond the deductible was free. In our benchmark treatment *LowPrice*, the deductible was set at 600 ECU. In this instance, subjects would need to pay for the first 12 treatment decisions and would have free treatment after that. The expenditures for leaving the sickness untreated, however, did not affect the deductible and subjects would always bear those costs. After every period, subjects received information about their accumulated income and, depending on the treatment, about their cumulated treatment costs and the remaining deductible.

The future price p_{it}^f in our experiment is defined as $p_{it}^f = 1 - Pr(h_{it})$, where $Pr(h_{it})$ is the probability of the event h , that an individual i at period t will hit the deductible by the end of the experiment if it treats all further sicknesses, regardless of the severity. The probability of hitting the deductible depends on the probability of falling sick (which is identical for all individuals in our experiment), the height of the deductible and the number of periods left in the game to hit the deductible.⁵ These parameters can be exogenously manipulated in the experiment between treatments to create variation in the future price. Within one treatment, the future price will be identical for each subject at period 0. With an increasing number of periods, subjects have direct influence on the future price through the extent of their health care utilization. Thus, our future price is based on this decision. The *spot price* in a given period is the same for all subjects until they hit the deductible since regardless of the treatment everyone faces the same chronology of health events. Hence we can generate variation in the future price while keeping the spot price constant and create conditions akin to the “ideal experiment” (Aron-Dine et al., 2015, p.726) in a simplified yet controlled setting.

For a simplified intuition, assume that individuals are risk neutral and look at two of several possible behavioral consequences.⁶ If an individual was completely myopic and would not look beyond the current period, it would never treat sickness B. This is equivalent to the optimal decision in a one-shot game (given that the deductible is not yet reached). On the other hand, a fully forward-looking individual that accounts for the entire duration of the game, would consider the cumulated budget and expected expenditures during the entire time span, and would optimize accordingly. With a sufficiently low future price, it could be thus optimal for a forward-looking individual to seek treatment for Sickness B and to initially pay the difference between its treatment and opportunity cost in order to reduce the deductible quickly and get free treatment afterwards. This is the case in our *LowPrice* treatments in which the future price is low enough at the beginning such that forward-looking and risk neutral individuals would always treat Sickness B. In contrast, in our *HighPrice* treatments the future price is high such that both, the myopic and the forward-looking individuals would decide against treating the mild Sickness B. In all treatments, a risk neutral individual would treat the severe Sickness A given only minimal amounts of forward-looking behavior. Only a completely myopic individual would be indifferent between seeking treatment or not.

⁵ Since we construct the future price under the assumption that all sicknesses are treated, it only matters if subjects are sick or healthy, not the severity of illness. Hence we can retrieve the future prices from the cumulative distribution function of the binomial distribution where the number of trials equals the number of periods and the number of successes is the number of treatments needed to hit the deductible, e.g. 12 for deductible of 600. The probability of being sick, regardless of severity, is $p = 0.4$.

⁶ Risk neutrality is also assumed in the models of Keeler et al. (1977), Aron-Dine et al. (2012), and Einav et al. (2015).

2.2 Treatments

Overall, we conducted seven treatments as shown in Table 3. The objective of the treatments *LowPrice*, *HighPricePeriods* and *HighPriceDed* was to investigate the relationship between future price and expenditure by keeping everything except the future price constant. In our benchmark treatment *LowPrice* the deductible was relatively low (600 ECU) over the duration of 52 periods. The likelihood of spending beyond the deductible was accordingly high, which implies a low future price (0.003). In *HighPricePeriods* we increased the future price by decreasing the number of periods to 26 and in *HighPriceDed* by increasing the deductible to 1150 ECU. Both manipulations led to similar future prices, 0.674 and 0.687 respectively. Treatments *LowPriceNoInfo* and *HighPriceNoInfo* aimed at investigating the role of information. Here subjects only learned their accumulated income and not the accumulated treatment costs and remaining deductible after each decision period. Treatment *LowPriceReverse* was a control treatment for order effects, in which we started with the health utilization decisions followed by the elicitation of risk and time preferences. Treatment *LowPriceNeutral* was an additional control treatment, in which the decision situation was framed in a neutral indemnity insurance context, with no association to health.

Table 3: Treatment Overview

Treatment	Deductible	# Periods	Future Price	<i>N</i>	Add. Info
<i>LowPrice</i>	600	52	0.003	48	Yes
<i>HighPricePeriods</i>	600	26	0.674	24	Yes
<i>HighPriceDed</i>	1150	52	0.687	24	Yes
<i>LowPriceNoInfo</i>	600	52	0.003	48	No
<i>HigPriceDNoInfo</i>	1150	52	0.687	24	No
<i>LowPriceReverse</i>	600	52	0.003	20	Yes
<i>LowPriceNeutral</i>	600	52	0.003	47	Yes
Total				235	

2.3 Experimental Procedure

The experiments were conducted at the Essen Laboratory for Experimental Economics (elfe) in Essen in 2016 and 2017. Sessions lasted about 90 minutes. Overall, 235 students (117 male and 118 female) participated the experiment. Participants were recruited by the online recruiting system ORSEE (Greiner, 2015). The procedure was as follows. Subjects were randomly assigned to their seats in the laboratory upon arrival. Previous to each part of the experiment, they were given the corresponding instructions and were given time to read the instructions and to ask comprehension questions. The latter were answered in private by the same one experimenter across all sessions. To assure subjects' understanding of the decision task in each part, they had to answer a set of control questions. The experiment did not start unless all subjects had answered the control questions correctly. At the end of the experiment, two subjects were randomly selected and were paid for one of their 30 decisions in the

risk preferences and the time preferences tasks. The random selection took place at the very end of the experiment to avoid income effects for the utilization behavior part of the experiment. In the utilization behavior part, every single subject was paid out and the average payoff was 26.60 EUR. The earnings were determined by the cumulated income from the utilization decision part of the experiment. It was the sum of periodic income after accounting for expenditures in sickness. Finally, subjects were asked to answer a short questionnaire with questions on demographics and questions related to their behavior in the previous decisions.

3. Results

3.1 Initial Aggregate Health Care Utilization Behavior

For the analysis of our results we focus predominantly on initial utilization behavior, i.e. the decisions to seek treatment or not, during the first 26 periods, for various reasons. First, the *ceteris paribus* condition over all treatments only holds for this span as *HighPricePeriods* has only 26 periods. Second, we want to keep the spot price constant across treatments. This is only the case before hitting the deductible. Afterwards, the spot price would be 0. Given our random draw of health events, the earliest possible period to hit the deductible of 600 is period 30 if all twelve sicknesses are treated at this point. By period 26, ten sickness events will have occurred, four times Sickness A and six times Sickness B (see Table 2).

Low Price vs. High Price

We begin the analysis by comparing the results of *LowPrice* and *HighPricePeriods*. This resembles the empirical strategy utilized by Aron-Dine et al. (2015) that compares individuals who join the same deductible plan at different times of the year. By reducing the number of periods from 52 to 26 while keeping everything else constant, subjects have less time to hit the deductible and face a higher future price. If subjects did not react to the future price, only the severe Sickness A would be treated (i.e. four treatment decisions overall) and we would not see a difference between the two treatments, as the order of health events is identical for the first 26 periods. If subjects behaved forward-looking, we would expect treatment for all health events in *LowPrice* that would result in 10 treatment decisions by period 26.

Table 4 provides information on the average number of treatment decisions (regardless of the severity of illness) and the respective treatment rates for the severe Sickness A and the mild Sickness B for each treatment. We see that the average number of treatment decisions by a subject is 8.15 (of possible 10) for *LowPrice*, while it is only 5.67 for *HighPricePeriods* over the first 26 periods. This difference is significant according to a two-sided Mann Whitney U-test (MWU) ($p=0.0002$). Thus, subjects treat significantly more when the future price is low. We can also infer that the difference stems from treatment decisions for the mild health events, Sickness B. While over 95 percent of severe Sickness A cases are treated in both treatments indicating that subjects recognize the dominant strategy

of doing so, treatment rates for Sickness B differ substantially across the two treatments. In particular, 71 percent of the mild cases B are treated when the future price is low although not treating would be cheaper in a one shot situation (30 ECU vs. 50 ECU). Compared to this, only 31 percent are treated when the future price is higher, i.e. the likelihood of spending beyond the deductible is low.

Table 4: Initial Behavior by Period 26 (After 10 Sickness Cases)

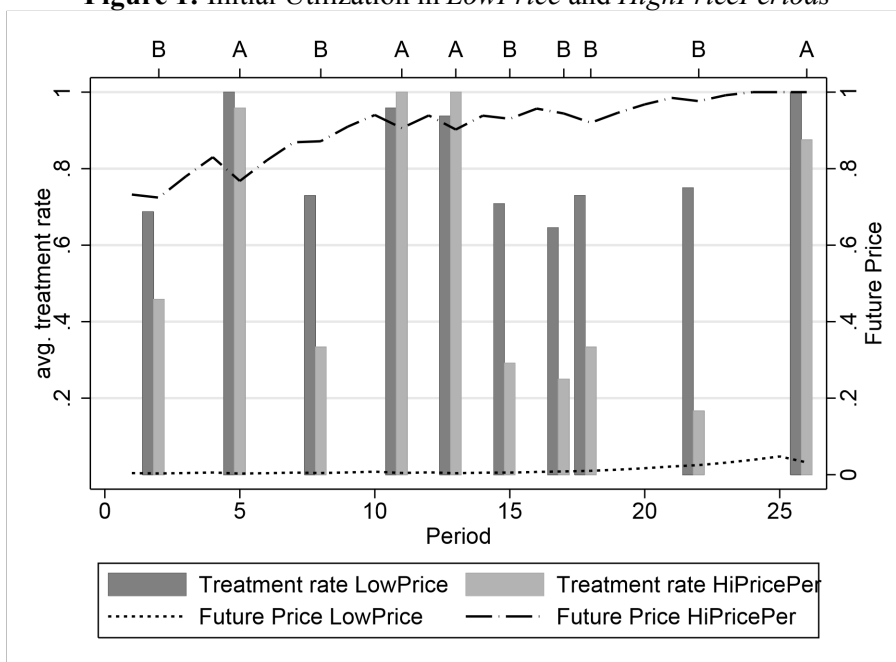
	Avg. number initial treatments	Treatm. rate for Sickn. A	Treatm. rate for Sickn. B
<i>LowPrice</i>	8.15 (2.55)	0.97	0.71
<i>HighPricePeriods</i>	5.67 (2.18)	0.96	0.31
<i>HighPriceDed</i>	5.04 (2.12)	0.94	0.22
<i>LowPriceNoInfo</i>	8.29 (2.47)	0.98	0.73
<i>HighPriceDNoInfo</i>	5.45 (2.77)	0.92	0.30
<i>LowPriceReverse</i>	8.10 (3.08)	0.90	0.75
<i>LowPriceNeutral</i>	8.34 (2.50)	0.96	0.75

Notes: s.d. in brackets. Treatment rate indicates share of respective sickness cases treated by all subjects. See Table A.5 in Appendix A.3. for results after 52 periods.

Figure 1 illustrates this pattern over time. The dark and light grey bars reflect the treatments rates in *LowPrice* and *HiPricePeriods* by sickness periods, while the dashed and the dash-dotted line visualize the average respective future prices accounting for utilization behavior. It is clearly visible that subjects treat mild cases B less when the future price is high. Moreover, we observe a significant negative time trend for treating Sickness B in *HighPricePeriods*.⁷ A higher future price due to a higher deductible in *HighPriceDed* also leads to a significantly lower number of treatments of 5.04 compared to *LowPrice* (MWU, p=0.0000). This result indicates that subjects do not only react to the spot price but also show forward-looking behavior and anticipate that they will spend beyond the deductible in *LowPrice*.

⁷ We run a random effects probit regression with the decision to see treatment or not in *HighPricePeriod* as the dependent variable and the respective Periods of Sickness B as independent variable. The coefficient is negative and significant on a level of 0.05. See Appendix A2.

Figure 1: Initial Utilization in *LowPrice* and *HighPricePeriods*



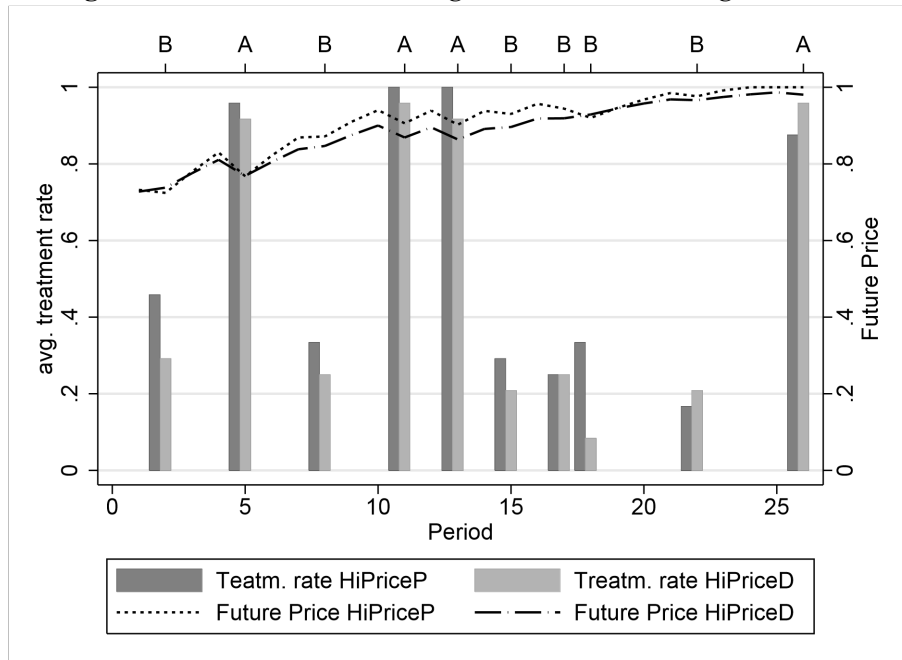
High Deductible vs. Fewer Periods

Next, we analyze whether subjects react differently when manipulating the future price through either more decision periods or a higher deductible. For this, we compare treatment behavior in *HighPricePeriods* with the one in *HighPriceDed*. If subjects reacted to the probability to hit the deductible, the differences between both treatments should be marginal as the future price is almost identical, 0.674 and 0.687. However, in *HighPricePeriods* the higher future price – or lower probability of hitting the deductible – is a product of halving the time to utilize the deductible while in *HighPriceDed* the price was manipulated by increasing the deductible from 600 to 1150. We find that the average number of treatments is 5.67 in *HighPricePeriods* and 5.04 in *HighPriceDed*. The difference is not significant ($p=0.3809$, MWU test two-sided). As we can see from Table 4, again, for both treatments the treatment rate in Sickness A is close to 100 percent. The treatment rate for Sickness B is similar between treatments and 31 percent in *HighPricePeriods* and 22 percent in *HighPriceDed*.

Figure 2 illustrates the dynamic relationship between treatment decisions and future price in these two treatments. The dotted and dashed lines in Figure 2 mark the respective average future prices for the two treatments over time accounting for past utilization behavior in every period. Since the future price is almost identical initially, the lines also have an almost identical starting point. Over time, they stay relatively close together while approaching the price of 1, i.e. the point where it is impossible to hit the deductible, towards period 26. The bars represent the respective treatment rates in *HighPricePeriods* and *HighPriceDed*. The difference in behavior between the two possible health events is clearly visible and for both *HighPrice* treatments the majority opts against treating when the mild Sickness B occurs. The result further supports the fact that subjects react to changes in the future price. As differences in behavior between the two *HighPrice* treatments are not significant and subjects seem to display a good

understanding of the future price overall. Whether the likelihood of hitting the deductible is manipulated via number of periods or height of deductible appears to be secondary. However, note that these results might be a consequence of the laboratory environment in which we the actual time horizons do not really differ.

Figure 2: Initial Utilization in *HighPricePeriods* and *HighPriceDed*



Information, Order and Framing Effects

To investigate the role of information on utilization behavior, we compare *LowPrice* and *LowPriceNoInfo*. In *LowPrice*, subjects received information on their income, their cumulated treatment costs, and their remaining deductible after each period. In *LowPriceNoInfo*, the information was reduced and the cumulated income update was the only feedback that subjects received. When we compare the initial utilization between both treatments, the information about the remaining deductible and cumulated treatment costs does not seem to lead to differences in utilization behavior (see Table 4). Utilization is almost identical, i.e. 8.15 in *LowPrice* compared to 8.29 *LowPriceNoInfo* and the difference is not significant ($p=0.8613$, MWU test two-sided). In a similar way the not giving information on the remaining deductible does not significantly affect the utilization when we compare *HighPriceDed* with *HighPriceDNoInfo* ($p=0.7071$, MWU test two-sided).

Finally, we control for the order and Framing. Reversing the order of part 1 and part 2, i.e. eliciting preferences after the insurance part, does not have a significant effect either. Utilization is 8.10 in *LowPriceReverse* and not significantly different from the benchmark treatment ($p=0.8858$, MWU test two-sided). In *LowPriceNeutral* we changed the wording of the instructions and the computer program and removed any association to health and framed it as general indemnity insurance. The average utilization is 8.34 and not significantly different from *LowPrice* ($p=0.7128$, MWU test two sided).

3.2 Individual utilization Behavior and Risk and Time Preferences

Heterogeneity in Utilization Behavior

In this section, we investigate individual behavior. Our controlled experimental design allows for classifying individuals as perfectly myopic or forward-looking based on their individual utilization behavior. Yet, this is only possible in the treatments with a low future price, as the behavioral prediction is identical for both types given a high future price, i.e. not to treat Sickness B. In the *LowPrice* treatments, however, decisions during Sickness B are a way to classify them. Before hitting the deductible, only forward-looking individuals would treat the mild cases Sickness B.

Table 5: Number of Subjects Displaying Myopic or Forward-Looking Behavior at Period 26

	Never treat B Myopic	In between	Always treat B Forward- looking	N
<i>LowPrice</i>	9 (18.75%)	11 (22.92%)	28 (58.33%)	48
<i>LowPriceNoInfo</i>	8 (16.67%)	12 (25.00%)	28 (58.33%)	48
<i>LowPiceRev</i>	3 (15.00%)	5 (25.00%)	12 (60.00%)	20
<i>LowPriceNeutral</i>	4 (8.51%)	15 (31.91%)	28 (59.57%)	47
<i>HighPricePer</i>	10 (41.67%)	11 (45.83%)	3 (12.50%)	24
<i>HighPriceDed</i>	13 (54.17%)	10 (41.67%)	1 (4.17%)	24
<i>HighPriceDNoInfo</i>	11 (45.83%)	8 (33.33%)	5 (20.83%)	24

From Table 5 we can infer that roughly 10 to 20 percent in the *LowPrice* treatments behave completely myopic and always decide against treatment for mild cases. Around 60 percent behave forward-looking and always treat Sickness B.⁸ Hence, in a scenario with a low future price (0.03) forward-looking behavior is very prevalent. Note that for completeness we included *HighPrice* treatments in Table 5. While classification of types is not possible, the low number of individuals treating

⁸ Thus, at least 70 percent of the individuals stick to one strategy, i.e. they always or never treat Sickness B in one of the treatments with a low price. When taking a closer look at the average treatment rates of the subjects who do not stick to one of the two strategies, we do not find a clear dynamical pattern in their behavior. Individual decisions patterns of these subjects show that few individuals decide against treating Sickness B at its first occurrence and always treat after which could be attributed to learning. However, for the majority this is not a plausible behavioral explanation.

Sickness B underlines our previous result that decisions to treat Sickness B are related to the height of the future price.

Individual Utilization and Risk and Time Preferences

We continue by investigating the relationship between elicited preferences from the first part and utilization behavior in the second part of the experiment. We are especially interested in whether and how forward-looking behavior relates to the individually elicited preferences. To outrule selection effects into treatments, we control for whether the distributions of subjects' risk and time preferences differed across treatments by running Kruskal-Wallis-Tests between treatments for risk preferences, the number of present oriented choices for time preferences as well as gender. However, we do not find significant differences ($p=0.5282$ for risk preferences, $p=0.2867$ for time preferences, and $p=0.2742$ for gender; values adjusted for ties, unadjusted values are higher). Hence, we can rule out that different subject pools with respect to risk and time preferences as well as gender drive differences in utilization behavior across treatments.

Subjects are classified as 'risk averse' if they made clearly risk averse choices in all risk elicitation tasks and thus met the criteria set by Holt and Laury (2002) (See Appendix A1). In our sample, 59.15 percent of all subjects can be classified as risk averse while 40.85 percent did not meet the criteria. With respect to time preferences subjects had a choice between an early payment after one week and a late payment in 5 weeks. While the late payment was fixed at 50 EUR, the early payment options descended from 49 to 4 EUR in intervals of 5 EUR with each decision row. Hence, participants had 10 choices between the two options and if they opted for the late payment at a low present value ('present' as in one week) they signaled a strong present bias (see Table A.3 in Appendix 1). The average number of early payment choices or the decision row after which subjects switched from the early to the late payment of 50 EUR was 1.756, so between the options of 44 and 39 EUR present value. We find a negative correlation between risk aversion and the switching point of time preferences (-0.1152), which is also weakly significant ($p=0.0781$; unadjusted significance level for pairwise correlation). Thus, risk averse individuals tend to opt for the late payment at higher present values which implies lower discount factors.

We start by analyzing the relationship between risk preferences and utilization behavior. From Table 6 we can see that risk averse types display more forward-looking health care utilization behavior, i.e. higher utilization, in *LowPrice*. Risk averse types have on average 8.89 treatment decisions compared to 7.10 by less risk averse subjects. This difference is significant ($p=0.0178$, MWU test). A similar pattern is descriptively observable in *LowPriceReverse*, however differences are not significant (MWU test: $p=0.6364$).⁹ In *LowPriceNoInfo*, however, the behavior by risk type observed in *LowPrice*

⁹ With the reversed order, income effects from the utilization part might have affected the elicitation of preferences. This could also be a reason why there are relatively fewer risk-averse subjects in this treatment than in the others.

almost completely disappears. Risk averse types initially treat 8.36 times which is not significantly different to the 8.13 treatment decisions by the others ($p=0.5012$, MWU test). The only difference between these two treatments is that subjects get no information on the height of the remaining deductible in *LowPriceNoInfo*. This observation suggests that risk preferences, forward-looking behavior and information are related. Higher risk aversion and higher utilization behavior only go alongside information on the remaining deductible is available. This difference is still significant after 52 periods ($p=0.0863$, MWU test) and is by then also observable for *HighPriceDed* and *HighPriceDNoInfo* (see Table A.6 in Appendix A.3). *LowPriceNeutral* is the only *LowPrice* treatment in which the pattern is the opposite, i.e. risk averse individuals treat significantly less than not risk averse on with 7.96 compared to 8.89 ($p=0.0785$, MWU test).¹⁰ Thus, while we find no effect of the framing on aggregate, the framing seems to affect the risk perception. With a health framing, risk averse types treat more which could imply a preference for not being exposed to financial risk in the future and are willing to invest for it, while in a neutral framing subjects seem to prefer ‘safe’ money in the present.

Table 6: Average initial number of treatment decisions by risk type

Risk-averse	<i>LP</i>	<i>HPPeriod</i>	<i>HPDed</i>	<i>LPNoInfo</i>	<i>HPDNoInfo</i>	<i>LPRev</i>	<i>LPNeutral</i>
Yes	8.89 (2.02)	5.31 (2.32)	5.38 (1.75)	8.36 (2.53)	5.75 (2.77)	8.67 (2.18)	7.96 (2.63)
N	28 (58.33%)	13 (54.17%)	16 (66.67%)	33 (68.75%)	12 (50%)	9 (45.00%)	28 (59.57%)
No	7.10 (2.88)	6.09 (2.02)	4.38 (2.72)	8.13 (2.39)	5.17 (2.86)	7.64 (3.70)	8.89 (2.23)
N	20 (41.67%)	11 (45.83%)	8 (33.33%)	15 (31.25%)	12 (50%)	11 (55.00%)	19 (40.43%)
Difference	1.79**	-0.78	-1	-0.23	0.58	1.03	-0.93*

Notes: s.d. in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *LP* stands for *LowPrice* and *HP* for *HighPrice*.

¹⁰ If we compare the utilization of risk types between treatment *LowPrice* and *LowPriceNeutral*, the differences are significantly for the non-risk averse (MWU, $p=0.0207$) and weakly significant for the risk averse ($p=0.0941$, MWU test).

On aggregate, the utilization between *LowPrice*, *LowPriceNoInfo* and *LowPriceNeutral* does not differ significantly but as we could see, how utilization is distributed among risk types differs significantly within the treatments. When the health situation is very salient with regular updates about the treatment costs and the remaining deductible as in *LowPrice*, risk averse subjects react differently than in the scenarios in which we either reduce the information to income updates or completely remove the health context. In the *HighPrice* treatments risk averse types tend to utilize less when there are fewer periods and more when the deductible is high, however, the differences are not significant (MWU tests: $p=0.1842$ for *HighPricePeriods*, $p=0.2040$ for *HighPriceDed*, $p=0.6251$ for *HighPriceDNoInfo*).

We continue by analyzing the relationship between utilization behavior and time preferences. We do not take a binary classification for time preferences but look at the number of early payment choices and instead of nonparametric tests we use a random effect probit model to look at the individual probability of treating the six occurrences of Sickness B in the first 26 periods while taking `present, i.e. the decision row after which subjects changed from early to late payment, as independent variable. We also control for risk aversion to support our previous nonparametric analysis. We do not find significant effects for any of the *HighPrice* treatments so we only report the results from the *LowPrice* treatments, which are more interesting with respect to behavior in treating Sickness B or not anyway. The regression results are presented in Table 7. The first column is based on the pooled observations from *LowPrice* and *LowPriceReverse* while the second and third column report the results for *LowPriceNoInfo* and *LowPriceNeutral* respectively. The regression results confirm our findings from the parametric analysis with respect to risk aversion.¹¹ Given sufficient information, risk averse subjects utilize significantly more in the treatments B with health framing and significantly less in the neutral framing. When we look at time preferences, we find that subjects with a higher discount factor and thus stronger present orientation behave less forward looking in the neutral framing. In other words, they have a stronger tendency to decide against paying the markup that makes hitting the deductible in the future more likely. We do not find significant effects in the treatments with health framing. Time preferences are elicited in tasks where subjects merely have to shift money between different points in time while in the health utilization tasks – albeit only by verbal framing – the implied stakes could be perceived also as non monetary. This might explain the significant correlation in the neutral framing where money is the only concern. Note that there is also disparity in relevant time horizons for the subjects between the insurance task and the time preferences task. While choices in the insurance task influence the payments within the duration of the experiment (i.e. 90 minutes) and also require a certain cognitive ability to understand the implication of current decisions on future outcomes, a choice between a payment in one or five weeks might be a very different kind of decision.

¹¹ Note that we included utilization for Sickness A and Sickness B in our nonparametric analysis while we only look at behavior in Sickness B in the random effect probit regression.

Table 7: Probability to Treat Mild Sickness B During First 26 Periods

	(1) <i>LP&LPRev</i>	(2) <i>LPNoInfo</i>	(3) <i>LPNeutral</i>
Risk aversion	2.169** (1.098)	0.809 (1.025)	-1.832** (0.782)
Present orientation	0.0837 (0.243)	-0.170 (0.310)	-0.316* (0.180)
_cons	1.271 (1.224)	2.321*** (0.893)	3.516*** (0.825)
/			
lnsig2u	2.605*** (0.381)	2.608*** (0.435)	1.494*** (0.430)
<i>N</i>	408	288	282
rho	0.931	0.931	0.817
sigma_u	3.678	3.684	2.111

Notes: The table presents results from a random effects probit regression where the dependent variable is the decision the mild Sickness B. Riskaversion is a binary variable and 'Present orientation' indicates the number of present oriented choices in the elicitation tasks and can take values from 0 to 10 (See Appendix A1 for details). *LP* stands for *LowPrice*.

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Other Influences on Utilization Behavior

Apart from the elicited risk and time preferences, we conducted a post experimental survey in which we collected basic socio demographic information and asked non-incentivized questions about risk preferences. We use some of the information to account for further variables that might influence utilization behavior. Like in the previous regression model, we investigate the probability to treat the mild Sickness B using random effects probit model. We pool observations from all treatments and look at the main treatment effects with respect to the future price first, i.e. deductible height and game duration. From the first column in Table 8 we can see that a high deductible leads to significantly lower utilization and a long game duration (52 periods) to a significantly higher one.¹² When adding further controls from the survey, we can see that females treat Sickness B significantly less. Overall, it is not too informative to pool all observations since predictions with respect to utilization are ambiguous but the effect of the main variables determining future price becomes visible.

To get a clearer picture, we again consider the treatments with the low future price and extend our analysis to all mild sickness cases during the 52 periods. We start by analyzing the effect of the main variations on treating Sickness B in column (1) of Table 9 and find that neither more information,

¹² 'High Deductible' is a dummy variable with 1 for deductible height 1150 and 0 for 600. 'Long Duration' is a dummy indicating overall duration of the experiment, i.e. 52 or 26 periods.

reversing the order or framing it neutrally has a significant effect overall. Given our different behavioral findings from the risk and time analysis, we then pool the subjects from *LowPrice* and *LowPriceReversed* in column (2) and compare them to the subjects from *LowPriceNeutral* in (3) with respect to the additional control variables. The period of the game has a significant positive effect. This is, however, not surprising since most subjects hit the deductible and have free care during the later stages in the low price treatments. The results further show that females utilize significantly less in both treatments (and also overall as seen in Table 8). Previous studies have found that females invest significantly less in investment games (see e.g. Charness and Gneezy, 2012, for a survey). Our experimental design for the utilization task could also be interpreted as an investment game where subjects invest present income into future financial benefit (free care). This could explain our findings. Charness and Gneezy (2012) conclude that women appear to be more financially risk averse. Our survey questions are somewhat informative here, since subjects who reported to be more risk loving with respect to financial investments utilize significantly more. However, our results for risk averse individuals where preferences were elicited in lottery tasks go into the opposite direction. It could be that our utilization task also captures loss aversion while in the lottery tasks subjects do not put realized income at stake. Finally, we see that subjects, who report to be more risk loving in the health domain, treat significantly less in the treatments with a health frame.

Table 8.: Probability to Treat Mild Sickness B– All Treatments 26 Periods

	(1) All treatments	(2) All treatments
High Deductible	-3.650*** (0.517)	-3.552*** (0.485)
Long Duration	3.230*** (0.674)	2.824*** (0.636)
Risk aversion		0.127 (0.365)
Present Orientation		-0.104 (0.0984)
Period		-0.000655 (0.00841)
Female		-1.165*** (0.370)
Priv. Health Insurance		-0.740 (0.546)
Risk loving (Financial Investments, Survey)		0.108 (0.0872)
Risk Loving (Health, Survey)		-0.106 (0.0695)
_cons	-1.313** (0.610)	-0.0820 (0.773)
/		
Insig2u	1.944*** (0.207)	1.815*** (0.200)
<i>N</i>	1410	1410
ρ	0.875	0.860
σ_u	2.643	2.478

Note: High Deductible' is a dummy variable with 1 for deductible height 1150 and 0 for 600. 'Long Duration' is a dummy indicating overall duration of the experiment, i.e. 52 or 26 periods. Risk aversion is a binary variable and 'Present orientation' indicates the number of present oriented choices in the elicitation tasks and can take values from 0 to 10 (See Appendix A1 for details). Period indicates the period of the game and can go up to 26 or 52. Risk Money and Risk Health were questions from a survey where subjects indicated how risk loving they were with respect to certain categories on a 10 point scale with 10 being very risk loving. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9.: Probability to Treat Mild Sickness B – *Lowprice* Treatments 52 Periods

	(1) <i>LP</i> Total	(2) <i>LP</i> & <i>LPRev</i>	(3) <i>LPNeutral</i>
Additional info	-0.126 (0.492)		
Reversed order	0.139 (0.663)		
Neutral	0.246 (0.492)		
Risk aversion		1.471** (0.749)	-2.358** (0.998)
Present orientation		0.0179 (0.192)	-0.580** (0.241)
Period		0.0182*** (0.00579)	0.0220*** (0.00724)
female		-2.293*** (0.711)	-1.980** (0.858)
Priv. Health Insurance		0.0661 (0.980)	0.309 (1.484)
Risk loving (Financial Investments, Survey)		0.320* (0.173)	0.419* (0.247)
Risk loving (Health, Survey)		-0.258* (0.147)	0.0140 (0.162)
_cons	2.703*** (0.353)	2.200** (0.880)	3.956*** (1.279)
/			
Insig2u	2.391*** (0.202)	2.063*** (0.315)	1.779*** (0.416)
<i>N</i>	2119	884	611
rho	0.916	0.887	0.856
sigma u	3.306	2.806	2.434

Note: *LP* stands for *LowPrice*. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4. Conclusions

The aim of this paper was to complement the empirical evidence on the effects of nonlinear deductible contracts on health care utilization behavior by using a controlled laboratory experiment. Compared to the field, the laboratory environment allowed us to control for keeping the spot price constant while varying the future price, as well as for other confounding factors such as seasonality, liquidity, or comorbidities. In the experiment, subjects went through a cycle of periods and were insured by a health plan with a deductible. In each period, they faced probabilistic health events and had to choose between treating or not. Using a sequential design we additionally elicited individual risk and time preferences for each subject in separate tasks similar to Andersen et al. (2008). This allowed for linking the latter to the observed health care utilization behavior.

In line with recent empirical results for nonlinear health insurance plans with deductibles (see e.g. Aron-Dine et al., 2015; or Brot-Goldberg et al., 2017), and for Medicare Part D plans (see e.g. Einav et al., 2015; Dalton et al., 2017; or Abaluck et al., 2015), we find that subjects respond to the embedded dynamic incentives and do not only react to the spot price. Whether the future price is manipulated through more decision periods or a higher deductible does not significantly affect utilization behavior as long as the likelihood to hit the deductible is the same. Classifying subjects according to utilization behavior, we find perfectly myopic as well as perfectly forward-looking individuals. Classifying them based on individually elicited risk preferences, we find that risk averse individuals behave more forward-looking than less risk averse individuals. However, this behavioral pattern only emerges if subjects are given sufficient information about the height of the remaining deductible. Our results contribute to further understanding utilization responses under dynamic incentives and confirm the previous findings from the field that there might be more than one relevant price elasticity as individuals react to different prices. They also emphasize the importance of acknowledging forward-looking behavior, risk preferences and information in this context.

References

- Abaluck, J. & Gruber, J. (2011). Choice inconsistencies among the elderly: Evidence from plan choice in the Medicare Part D program. *American Economic Review*, 101(4), 1180-1210.
- Abaluck, J., Gruber, J., & Swanson, A. (2015). Prescription drug utilization under Medicare Part D: A dynamic perspective. *NBER Working Paper* 20976.
- Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3), 583-618.
- Andreoni, J., Kuhn, M. A., & Sprenger, C. (2015). Measuring time preferences: A comparison of experimental methods. *Journal of Economic Behavior & Organization*, 116, 451-464.
- Aron-Dine, A., Einav, L., & Finkelstein, A. (2013). The RAND health insurance experiment, three decades later. *Journal of Economic Perspectives*, 27(1), 197-222.
- Aron-Dine, A., Einav, L., Finkelstein, A., & Cullen, M. R. (2012). Moral hazard in health insurance: How important is forward looking behavior? *NBER Working Paper* 17802.
- Aron-Dine, A., Einav, L., Finkelstein, A., & Cullen, M. (2015). Moral hazard in health insurance: do dynamic incentives matter? *Review of Economics and Statistics*, 97(4), 725-741.
- Bhargava, S., & Manoli, D. (2015). Psychological frictions and the incomplete take-up of social benefits: Evidence from an IRS field experiment. *The American Economic Review*, 105(11), 3489-3529.
- Brot-Goldberg, Z. C., Chandra, A., Handel, B. R., & Kolstad, J. T. (2017). What does a deductible do? The impact of cost-sharing on health care prices, quantities, and spending dynamics. *The Quarterly Journal of Economics*, 132(3), 1261-1318.
- Cardon, J. H. & Hendel, I. (2001). Asymmetric information in health insurance: evidence from the national medical expenditure survey. *RAND Journal of Economics*, 32(3), 408-427.
- Charness, G., & Gneezy, U. (2012). Strong evidence for gender differences in risk taking. *Journal of Economic Behavior & Organization*, 83(1), 50-58.
- Dalton, C. M. (2014). Estimating demand elasticities using nonlinear pricing. *International Journal of Industrial Organization*, 37, 178-191.
- Dalton, C. M., Gowrisankaran, G., & Town, R. (2017)/(2015). Salience, Myopia, and Complex Dynamic Incentives: Evidence from Medicare Part D. *NBER Working Paper* 21104. NKS: There is an older NBER WP from (2015). The 2017 version is only available via their homepage
- Einav, L., Finkelstein, A., & Schrimpf, P. (2015). The response of drug expenditure to nonlinear contract design: Evidence from Medicare Part D. *Quarterly Journal of Economics*, 130(2), 841-899.
- Ellis, R. P. (1986). Rational behavior in the presence of coverage ceilings and deductibles. *The RAND Journal of Economics*, 17(2): 158-175.
- Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J.P., Allen, H., Baicker, K. & Oregon Health Study Group (2012). The Oregon health insurance experiment: evidence from the first year. *Quarterly Journal of Economics*, 127(3), 1057-1106.

- Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with ORSEE. *Journal of the Economic Science Association*, 1(1), 114-125.
- Hastings, J. S., & Weinstein, J. M. (2008). Information, school choice, and academic achievement: Evidence from two experiments. *Quarterly Journal of Economics*, 123(4), 1373-1414.
- Holt, C. A. & Laury, S. K. (2002). Risk aversion and incentive effects. *The American Economic Review*, 92(5), 1644–1655.
- Keeler, E. B., Newhouse, J. P., & Phelps, C. E. (1977). Deductibles and the demand for medical care services: The theory of a consumer facing a variable price schedule under uncertainty. *Econometrica*, 45, 641–655.
- Keeler, E. B. & Rolph, J. E. (1988). The demand for episodes of treatment in the health insurance experiment. *Journal of Health Economics*, 7(4), 337–367.
- Kling, J. R., Mullainathan, S., Shafir, E., Vermeulen, L. C., & Wrobel, M. V. (2012). Comparison friction: Experimental evidence from medicare drug plans. *The Quarterly Journal of Economics*, 127(1), 199–235.
- Kowalski, A. E. (2015). Estimating the tradeoff between risk protection and moral hazard with a nonlinear budget set model of health insurance. *International Journal of Industrial Organization*, 43, 122–135.
- Loewenstein, G., Friedman, J.Y., McGill, B., Ahmad, S., Linck, S., Sinkula, S., Beshears, J., Choi, J.J., Kolstad, J., Laibson, D. & Madrian, B.C. (2013). Consumers' misunderstanding of health insurance. *Journal of Health Economics*, 32(5), 850-862.

A Appendix

A.1 Price Lists for Risk and Time Preferences

The following tables display the tasks subjects had to play for the elicitation of risk and time preferences. Subjects had to decide between Option A and Option B in every row. The (expected) payoff differences were not displayed to them. Mostly in line with Holt and Laury (2002) we classified subjects as risk averse if they made at least six safe choices (Option A) in Lottery A and at least five safe choices in Lottery B.

In the time preferences task subjects had to decide between different amounts of money to be transferred on their bank account after one or five weeks. We delayed the early payment to account for the process of transferring the money. Also we used bank transfers for the early and late payment to keep the transaction costs constant. If the early payment would have been paid immediately in cash, subjects might have preferred it for convenience reasons. We capture the time preferences by simply looking at the number of times subjects preferred the early over the late payment, starting from the top. Hence, this 'present orientation' can take values from 0 to 10.

At the end of the experiment one person per session was randomly selected to get paid for one random decision the risk task and one person for a random decision in the time task. This procedure happened at the very end of the experiment to avoid income effects that could confound behavior in the second part. The joint elicitation of risk and time preferences follows Andersen et al. (2008).

Table A 1: Risk Lottery A

	Option A		Option B		Expected payoff difference
	20 EUR	16 EUR	38.50 EUR	1 EUR	
1	10%	90%	10%	90%	11.65 EUR
2	20%	80%	20%	80%	8.30 EUR
3	30%	70%	30%	70%	4.95 EUR
4	40%	60%	40%	60%	1.60 EUR
5	50%	50%	50%	50%	-1.75 EUR
6	60%	40%	60%	40%	-5.10 EUR
7	70%	30%	70%	30%	-8.45 EUR
8	80%	20%	80%	20%	-11.80 EUR
9	90%	10%	90%	10%	-15.15 EUR
10	100%	0%	100%	0%	-18.50 EUR

Table A.2: Risk Lottery B

	Option A		Option B		Expected payoff difference
	22.50 EUR	15 EUR	40 EUR	5 EUR	
1	10%	90%	10%	90%	7.25 EUR
2	20%	80%	20%	80%	4.50 EUR
3	30%	70%	30%	70%	1.75 EUR
4	40%	60%	40%	60%	-1 EUR
5	50%	50%	50%	50%	-3.75 EUR
6	60%	40%	60%	40%	-6.50 EUR
7	70%	30%	70%	30%	-9.25 EUR
8	80%	20%	80%	20%	-12.00 EUR
9	90%	10%	90%	10%	-14.75 EUR
10	100%	0%	100%	0%	-17.50 EUR

Table A.3: Time Preferences Task

Option A:	Option B	Difference
Payment in one week	Payment in five weeks	
49 EUR	50 EUR	1 EUR
44 EUR	50 EUR	6 EUR
39 EUR	50 EUR	11 EUR
34 EUR	50 EUR	16 EUR
29 EUR	50 EUR	21 EUR
24 EUR	50 EUR	26 EUR
19 EUR	50 EUR	31 EUR
14 EUR	50 EUR	36 EUR
9 EUR	50 EUR	41 EUR
4 EUR	50 EUR	46 EUR

A.2. Time Trend in HighPricePeriods**Table A.4: Probability to Treat Sickness B in *HighPricePeriods***

	(1)
Period	-0.0711*** (0.0249)
_cons	-0.115 (0.530)
/	
lnsig2u	1.275** (0.580)
<i>N</i>	144
rho	0.782
sigma u	1.892

Notes: Random effect probit regression with participant's decision to seek treatment in the six cases of Sickness B during 26 periods is dependent variable.

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.3 After 52 Periods

Table A.5: Behavior by Period 52 (After 22 Sickness Cases; 9x A; 13xB)

	Avg. number treatments	Treatm. rate for Sickn. A	Treatm. rate for Sickn. B
LowPrice	18.38 (5.11)	0.98	0.73
HighPriceDed	10.46 (3.60)	0.94	0.15
LowPriceNoInfo	18.54 (5.28)	0.98	0.75
HighPriceNoInfo	11.33 (5.09)	0.93	0.23
LowPriceReverse	17.70 (7.08)	0.88	0.75
LowPriceNeutral	18.68 (5.51)	0.96	0.78

Notes: s.d. in brackets. Treatment rate indicates share of respective sickness cases treated by all subjects.

Table A.6: Average Number of Treatment Decisions by Risk Type After 52 Periods

Risk averse	LowPrice	HPriceDed	LPriceNoInfo	HPriceNoInfo	LPriceRev	LPriceNeut
Yes	19.57 (4.32)	11.19 (2.90)	18.82 (5.05)	11.42 (4.68)	19.67 (4.39)	18.00 (6.01)
n	28	16	33	12	9	28
No	16.70 (5.73)	9.00 (4.57)	17.93 (5.90)	11.25 (5.67)	16.09 (8.57)	19.68 (4.67)
n	20	8	15	12	11	19
Diff	2.87**	1.19*	0.89	0.17	3.58	-1.68*

Notes: s.d. in brackets. *HighPricePeriods* omitted since it ended after 26 periods. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$