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Preface

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Bern, August 2024 *Fabienne Loetscher*

Contents

List of Figures

List of Tables

Introduction

Designing effective policies to improve efficiency in health care markets while ensuring public health is challenging. Most policies aim to incentivize certain desired behaviors among various actors in the health care market. However, policies often have unintended consequences, as different individuals and firms might react differently to the same policy. Therefore, the analysis of (i) responses to past policy changes, (ii) the identification of potentially misaligned incentives in the current system, and (iii) the elicitation of preferences to predict responses to potential future policies reveal important information for optimal policy design.
In this thesis, I focus on policy design in the health care sector. Health care markets and health policy offer an excellent laboratory to study the effectiveness of past, current and potential future policies for two reasons. First, health care markets are highly regulated. Second, in the light of increasing health care costs among most developed countries, it is essential to develop effective policies to contain health care expenditure while avoiding possible adverse effects on public health.
This thesis studies how individuals and firms react to policy reforms and the incentives generated by existing policy structures. The first two articles focus on optimal health plan design in health insurance and use detailed claims-level health insurance data. The third article concentrates on the creation of effective policies to deter individuals from engaging in behaviors detrimental to their health. This third analysis is based on data retrieved from a discrete choice experiment.

In the first article of this thesis, I analyse jointly with Michael Gerfin and Christian Schmid how higher out-of-pocket payments for expensive drugs affect pharmaceutical firms' pricing behavior and patients' drug demand. To do so, we study the effects of a policy change in Switzerland in 2011, which introduced a higher coinsurance rate of 20% (instead of the regular 10%) for substitutable prescription drugs with a price above a predefined threshold. We find that firms considerably reduced their prices to avoid higher coinsurance on their products. Whereas generic producers reduced the prices for 84% of their affected products, brand-name producers were much more reluctant to lower prices. To estimate the demand response of the policy, we exploit the delayed implementation of the policy by one Swiss health insurer

in a differences-in-differences framework. Our results suggest that patients slightly reduced their demand for products subject to higher coinsurance. Without the anticipatory behavior of firms, however, the demand response would likely have been more pronounced, emphasizing the importance of the interplay of different actors in the health care market. Furthermore, the heterogeneity in price responses was mirrored in the demand responses. While higher out-of-pocket payments hardly reduced the probability of purchasing affected brand-name drugs, the demand response was more pronounced for generics with higher coinsurance. In summary, our findings suggest that (re)establishing market-like mechanism such as price signals can be effective in enhancing health care market efficiency. Consequently, our results provide valuable information for designing effective cost-sharing structures in health care.

In the second article, I study, together with my coauthors Caroline Chuard and Christian Schmid, whether individuals are forward-looking in their health care consumption, taking into account future price changes. For this purpose, we use a natural experiment. We exploit the exogenous increase in cost-sharing for individuals upon reaching adulthood in Switzerland. Our results provide suggestive evidence that individuals increase their health care consumption anticipating future out-of-pocket price increases. Exploratory analyses further indicate that the higher health care demand in the last year with lower out-of-pocket prices is more likely extra demand than demand shifting across periods. Our findings have important policy implications, revealing that individuals react to misaligned dynamic incentives created by a discontinuous change in the out-of-pocket price around the turn of the year. Therefore, our findings may guide policymakers in adjusting annual deductible structures to enhance cost-sharing effectiveness.

In the last article, I assess jointly with my coauthors Anna Nicolet, Catherine Maclean, Joachim Marti, and Michael Pesko, the effectiveness of various proposed tobacco market policies in reducing smokers' consumption of health-harming tobacco products. Specifically, we study preference heterogeneity across different types of smokers and elaborate on its significance for optimal policy design. Our findings indicate that there is considerable heterogeneity in preferences for the various tobacco and smoking cessation products considered, leading to different responses of distinct smoker types towards proposed tobacco policies. While more than 50% of smokers have a strong preference for cigarettes and hardly react to any policy, two subgroups of smokers seem more sensitive to tobacco policies. Our analyses further suggest that, for several policies, there is a trade-off between the policy's health benefits for one subgroup of smokers and unintended consequences for another subgroup of smokers. Hence, considering this heterogeneity and understanding the underlying drivers thereof, is crucial for the design of effective tobacco market regulations.

Chapter 1

The effect of higher out-of-pocket payments on drug prices and demand

joint with Michael Gerfin and Christian Schmid

Abstract

Health care markets often lack a market force because the presence of health insurance undermines price signals. Patients have little incentive to shop for low-priced alternatives because they do not bear the full cost of their health care consumption. In turn, producers lack incentives to compete on prices. To improve efficiency in the pharmaceutical market, Switzerland introduced out-of-pocket price differentiation. As of July 1st 2011, substitutable pharmaceuticals with prices above a predefined threshold became subject to 20% coinsurance instead of the regular 10% coinsurance. Using comprehensive price data from public sources and patient drug use data from two Swiss health insurers, we analyze the price and demand response of this policy. Our analysis reveals an average pharmaceutical firm price reduction of 11%, with a more pronounced response from generic producers than from firms producing brand-name drugs. Regarding demand, we exploit a natural experiment in which one health insurer failed to timely implement the 20% coinsurance policy, resulting in quasi-random exposure to higher coinsurance. For patients affected by the policy, we find that the likelihood of purchasing a 20% coinsurance drug decreases by 4.3 and 1.3 percentage points for generic and brand-name drugs, respectively. These demand response estimates constitute lower bounds, as without the anticipatory behavior of producers, the demand response would likely have been more pronounced. Hence, our results indicate that the policy's effectiveness is based on the interaction between price-sensitive demand and profit-maximizing firms. Overall, our findings suggest that the (re)introduction of market-like mechanisms, such as price signals, can be effective in improving health care market efficiency.

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1.1 Introduction

Health insurance reduces financial risks for patients but also undermines price signals. Patients with insurance coverage do not pay the full price of their health care consumption out-of-pocket. Therefore, their incentive to shop for lower-priced alternatives is low, implying that health care providers and producers of health care goods have little incentive to compete on prices. Consequently, health care markets often lack a price mechanism to ensure the efficient allocation of resources. This lack of a market force may also explain the price differences between homogeneous goods often observed in the health care market, such as equivalent medical supplies and devices, identical laboratory services, and pharmaceutical products. Improving price signals by introducing differential cost-sharing is expected to restore price competition, influencing both supply and demand, because the supply side must account for the potential response in demand. Thus, introducing out-of-pocket price differentiation is a promising tool for enhancing efficiency in the health care market.

The pharmaceutical market seems well suited to use out-of-pocket price differentiation as an allocation instrument. First, there are therapeutically equivalent products. Therefore, the choice of the drug is not confounded by medical considerations. Second, patients have more control over the choice of drugs than, for instance, the choice of laboratory services. In recent years, patients purchasing pharmaceuticals have become increasingly exposed to out-of-pocket price differences. Today, most European countries apply reference price systems, within which patients must pay any difference between the drug price and its reference price out-of-pocket. Because the reference price depends on the price of cheaper alternatives, out-of-pocket expenditures are higher for patients purchasing expensive pharmaceuticals. In the United States, Medicare Part D assigns prescription drugs to one of up to five tiers, across which cost-sharing varies. Higher-priced drugs are usually assigned to a tier with higher cost-sharing as long as cheaper alternatives are available. Similarly, in Switzerland, a higher coinsurance rate is applied to expensive drugs, whereas a lower rate is charged for low-cost drugs.

In this study, we analyze the supply and demand effects of the introduction of this "two-tiered" coinsurance rate for substitutable drugs in Switzerland in 2011. Switzerland is especially interesting because pharmaceutical consumption is relatively low compared to other OECD countries, and pharmaceutical expenditures are mainly driven by high prices and the high market share of expensive (brand-name) drugs (Paris and Docteur, 2007). Specifically, we study the pharmaceutical firms' price and the patients' demand reactions in response to the 2011 reform. As of July 1st 2011, expensive generic and brand-name drugs became subject to 20% instead of 10% coinsurance if sufficient less expensive generic alternatives were available.[1] This policy triggered producers and consumers to respond sequentially. First, in the early

[1] In 2006, a similar policy was implemented but only applied to 23 brand-name drugs. In 2011, the policy was extended to generics and additional brand-name drugs (269 affected products).

spring of 2011, firms were informed whether their product is intended to be subject to 20% coinsurance starting July 2011, and were given the opportunity to reduce prices to avoid high coinsurance on their products. Second, patients could react to the higher coinsurance rate on products for which firms decided not to reduce their prices. The implementation of the two-tiered coinsurance rate in mid 2011, which did not affect all drugs per active pharmaceutical ingredient, provides an ideal setup to analyze price responses. To study the policy's effect on drug prices, we use the list of drugs covered by mandatory health insurance published monthly by the Federal Office of Public Health (FOPH). The list contains the drugs' ex-factory and retail prices and comprehensive information on drug characteristics.[2] Moreover, we exploit a natural experiment − the delayed implementation of the policy by one health insurer − to identify demand responses. To do so, we have access to detailed drug claims data from two Swiss health insurers, which covered 23.5% of the entire Swiss population in 2011.

Our results suggest that to avoid the 20% coinsurance rate, pharmaceutical firms reduce their drug prices on average by 11%. The price reaction is more pronounced among firms producing generics, whose prices are reduced for roughly 84% of affected products. Producers of brand-name drugs are 1.8 times less likely to reduce prices. In terms of demand responses, our findings indicate that the (higher) 20% coinsurance rate promotes the substitution of expensive drugs with their cheaper alternatives. Specifically, the likelihood of purchasing a drug subject to 20% coinsurance decreases by 4.3 percentage points for generics and 1.3 percentage points for brands. Patients who purchase generic drugs appear to be price sensitive. They tend to switch to cheaper generic options in response to differentiated cost-sharing. In contrast, patients purchasing brand-name drugs seem to be less price sensitive. The estimated modest substitution behavior is likely a lower bound, as pharmaceutical firms anticipate patients' demand responses and lower their prices.

Our study complements the existing evidence on the effects of differences in out-of-pocket payments for pharmaceuticals on prices and quantities (Brekke et al., 2011; Herr and Suppliet, 2017; Pavcnik, 2002). In line with our results, previous studies report that exposing patients more strongly to actual price differences significantly reduces drug prices and increases the market share of cheap generic drugs (Brekke et al., 2011; Kaiser et al., 2014; Pavcnik, 2002). Moreover, consistent with our findings, Herr and Suppliet (2017) find higher price sensitivity among patients who purchase generics. Prior studies focus on differentiated out-of-pocket costs in the context of reference price systems, whereas we study the impact of a differentiated coinsurance rate. Furthermore, our setting enables us to isolate the patient-driven demand response, while the existing literature measures a combined response driven by both patients and providers (i.e., physicians and pharmacists).

[2]Ex-factory price: price charged by the pharmaceutical firm, excl. transportation costs. Retail price: final price paid by the patient or insurer, incl. distribution markups by providers (pharmacies, physicians, and hospitals).

The present analysis is further related to the research on generic substitution. This strand of literature finds that generic substitution is more likely among patients with higher out-of-pocket payments (Dalen et al., 2011; Decollogny et al., 2011; Lundin, 2000). Moreover, larger price differences between branded and generic versions promote generic substitution (Decollogny et al., 2011). Habit-persistence in physicians' prescribing behavior and patients' attachment and subjective beliefs about the quality of products might explain part of the observed price differences for homogeneous pharmaceutical products (Coscelli, 2000; Dalen et al., 2011). Additionally, Hjalmarsson et al. (2024) show that a lack of information on the availability of cheaper alternatives partly explains the low rates of generic substitution in Switzerland. We expand on the existing evidence in two regards. First, we focus not only on the substitution of brand-name drugs with their generic versions, but also on the substitution between generic options with different prices. Second, our results suggest that price signals induced by differentiated cost-sharing may help to break habits or raise awareness of the availability of more cost-effective options. In a broader context, we contribute to the literature on steering health care demand toward more cost-effective options outside the pharmaceutical market. Ackley's results (2022) suggest that tiered cost-sharing successfully lowers per-episode costs while not reducing the likelihood of seeking care. This coincides with the aim of the policy examined in this study: the substitution of more expensive drugs with cheaper alternatives, without reducing overall demanded quantities.

The remainder of this chapter is organized as follows. Section 1.2 provides information on Switzerland's institutional background, drug pricing, and the two-tiered coinsurance policy. In Section 1.3, we discuss the price response of pharmaceutical firms and in Section 1.4, we present the demand response of patients. In particular, we describe the quantity data in 1.4.1 and discuss the natural experiment and our identification strategy in 1.4.2. In Section 1.4.3, we report the descriptive statistics on pre-treatment drug demand and background characteristics, and present the results in 1.4.4. Finally, Section 1.5 provides a brief discussion of the results and concludes the chapter.

1.2 Institutional background

1.2.1 Health insurance and patient cost-sharing

The Swiss health care system is based on the principles of regulated competition, as in Germany, the Netherlands, and the U.S. marketplaces in the Affordable Care Act (ACA) (Schmid et al., 2018).[3] Health insurers and providers compete on price and quality, while regulations ensure risk solidarity, individual affordability of health plans, and equal access to health care. Health

[3]The following description draws heavily on Schmid et al. (2018).

insurance is mandatory, but consumers can freely choose among more than 50 private insurers (open enrollment). Mandatory health insurance must cover the same standardized package of health care services. Regarding prescription drugs, health insurance covers the drugs listed on the so-called *specialities list*, which is compiled and published monthly by the Federal Office of Public Health (FOPH).[4]

All health care services covered by mandatory health insurance are subject to patient cost-sharing. The standard health insurance plan includes a deductible of CHF 300, but consumers can opt for a higher deductible ranging from CHF 500 to CHF 2,500. A coinsurance rate of 10% applies to all costs exceeding the chosen deductible, up to a stop-loss amount of CHF 700. There is a single exception to the 10% coinsurance rate. If multiple drugs with the same active pharmaceutical ingredient, strength, and galenic form (referred to as *substitution group*) are listed on the specialities list, the coinsurance rate can be 20% (for details, see below). In this case, the patient pays 20% of the drug's retail price out-of-pocket. However, this higher coinsurance rate applies only if the patient has already exceeded the deductible and is still below the stop-loss amount.[5]

1.2.2 Drug pricing and periodic price reviews

As the 20% coinsurance is determined by price differences between substitutable drugs, we provide a brief overview of prescription drug pricing in Switzerland. The launch prices of new brand-name drugs are based on a combination of internal and external reference pricing. In internal reference pricing, the FOPH considers the efficacy and cost of a new drug relative to drugs that are already used in Switzerland to treat the same disease. In external reference pricing, the FOPH calculates the average ex-factory price of the new brand-name drug in several reference countries.[6] The ex-factory price in Switzerland is given by a weighted average of this internal and external reference price. In contrast, the launch prices of generics are determined by the price and market volume of the corresponding brand-name drug. In general, the larger the brand's market volume, the lower the generic price level.[7]

After the market launch, ex-factory drug prices of brand-name drugs and their generic alternatives are reviewed every third year. In 2011, these periodic price reviews were conducted in January and November, each time for a different subgroup of drugs. The price review for brand-name drugs is based on external reference pricing and, since 2015, additionally on inter-

[4] A prerequisite for the inclusion of a drug in the specialities list is the drug's approval by Swissmedic, which is the national authorization authority for drugs.

[5] Importantly, only 15% of the drug price, not the paid 20%, counts toward the patient's stop-loss. This ensures that the patients' out-of-pocket expenses are larger, even if they reach the stop-loss.

[6] Today, this includes nine countries: Austria, Belgium, Denmark, Finland, France, Germany, Sweden, the Netherlands, and the United Kingdom.

[7] For instance, if the brand's average annual market volume was between four and eight million Swiss francs in the three years before patent expiration, the generic's price has to be at least 30% below the brand's price.

nal reference pricing, whereas the price review for generics maintains a price spread between the generic and the corresponding brand-name drug. Consequently, drug prices are heavily regulated and decreasing in a stepwise manner over time.

The retail price is given by the ex-factory price plus two distribution margins, which are specified in a FOPH bylaw (see Table 1.C.1 in the Appendix). These distribution margins are increasing in the drug price, incentivizing providers to offer the more expensive drugs to their patients. Importantly for our demand analysis, physicians prescribe an active pharmaceutical ingredient, a galenic form and a strength (i.e., a substitution group), often by writing the name of the corresponding brand-name drug on the prescription. However, patients are free to choose any product within this substitution group. In fact, in Switzerland, health care providers are obliged to inform their patients about the availability of cheaper alternatives.

1.2.3 The two-tiered coinsurance policy

Despite lower prices, the demand for generics in Switzerland has been relatively low compared to that in other European countries (see e.g., Trüb, 2021). Moreover, pharmaceutical prices were persistently high even for certain generics. To encourage the substitution with cheaper alternatives by patients and physicians, and to incentivize price reductions by pharmaceutical firms, the FOPH introduced a higher coinsurance rate for substitutable drugs with a retail price above a predefined threshold. This two-tiered coinsurance policy, described in Table 1.A.1, involved substitution groups comprising of at least three drugs.[8] Specifically, substitutable drugs became subject to 20% coinsurance in July 2011 if their retail price was at least 20% higher than the average retail price of the cheapest third in their substitution group.[9] Moreover, as prices per unit (e.g., per pill) vary with package size, the best-selling package size within the substitution group, the so-called *modal package*, is used to determine the average price of the cheapest third. Multiplying this average price by 1.2 gives the substitution group's threshold, which is published by the FOPH roughly two months before its implementation. This gives pharmaceutical firms time to respond with a price reduction to avoid 20% coinsurance. The timeline in Figure 1.A.1 provides an overview of the policy implementation in 2011, which is the focus of this study.[10] We only briefly discuss responses to annual updates of the thresholds. Furthermore, until 2017, firms were required to only reduce the price of the modal package to avoid 20% coinsurance on all corresponding package sizes. We therefore focus on modal packages in the analyses of price responses in the next section and provide information on the price development of non-modal packages in the Appendix (see Section 1.B).

[8] This ensures that patients have the option to switch to products with regular coinsurance of 10%.

[9] For an example and a more detailed explanation of the policy, see Appendix Section 1.A.1.

[10] In 2006, a similar policy was implemented but applied only to a subset of brand-name drugs. These drugs that have been affected by the policy in 2006 are excluded from our analyses of demand effects and considered separately in our analyses of price responses (see Table 1.B.2 in the Appendix).

1.3 Price response of pharmaceutical firms

1.3.1 The market for substitutable drugs

To analyze the firms' price reactions to the policy, we use monthly data on pharmaceutical prices provided by the FOPH. This publicly available specialities list contains information on all the pharmaceutical products covered by mandatory health insurance. A pharmaceutical product is defined as a drug produced by a particular pharmaceutical firm with a specific active ingredient, galenic form, strength, and package size. The list includes a unique product identifier (*Swissmedic number*). For each product, we also observe the monthly ex-factory and retail prices, whether it is a brand-name drug or a generic version, and whether it is subject to 20% coinsurance in a given month. Upon request, the FOPH provided additional data to determine the threshold, particularly the information on the modal package size.

In July 2011, the specialities list consisted of 8,641 products with 1,383 distinct active pharmaceutical ingredients and 3,150 substitution groups. Among these 3,150 substitution groups, for 242 (or 8%) existed at least three substitutes. These 242 substitution groups corresponded to 19% in terms of prescription drug costs.[11] Hence, the 20% coinsurance regulation targeted frequently used, off-patent prescription drugs.

Henceforth, we focus on the substitution groups targeted by the policy, that is, those for which at least three clinically proven substitutes existed on the Swiss market in June 2011. Within these targeted substitution groups, 269 modal packages had a price above their substitution group-specific threshold in June 2011, and were thus threatened with a higher coinsurance rate after the policy implementation (see Table 1.1). These products are referred to as the *affected* drugs.[12] Low-cost alternatives with prices below the threshold for the 20% coinsurance rate, hereafter referred to as the *unaffected* drugs, accounted for approximately 39.6% of the products.[13] Although the share of affected products was only 8.7%, the pre-reform market share of these products in terms of claimed packages was 20.4%. Hence, affected products were frequently purchased before the policy. The pre-reform market share of below-threshold alternatives was 48.5%.

Considerable price differences are observed within each substitution group. Table 1.1 indicates that the pre-reform average ex-factory price per package of affected drugs is roughly 1.8-times the average price of unaffected drugs. A comparison with the corresponding retail prices reveals that pharmacists and physicians have an incentive to dispense more expensive (affected) drugs because the average markup is CHF 25.1 which is considerably larger than the CHF 19.3

[11] To calculate shares in terms of drug costs, we use health insurance claims data described in Section 1.4.1.
[12] Appendix Table 1.B.1 provides an overview of all product groups differently impacted by the policy.
[13] Table 1.1 does not show descriptive statistics on non-modal packages, exempted drugs and drugs already subject to 20% coinsurance before July 2011, which explains why the percentages do not add up to 100 percent. Table 1.B.2 in the Appendix provides a complete overview.

for below-threshold (unaffected) alternatives. Moreover, generic products are less likely to be affected by the policy than brand-name products (6.63% vs. 21.4%).

Table 1.1: Pre-reform prices of (un-)affected drugs

	Affected	Unaffected
Ex-factory price (CHF), mean (sd)	70.1 (119)	38.8 (48.2)
Retail price (CHF), mean (sd)	95.2 (138)	58.0 (57.4)
Number of products, N (%)	269 (8.70)	1,221 (39.6)
Number of generics, N (%)	176 (6.63)	1,125 (42.4)
Number of brands, N (%)	93 (21.4)	96 (22.1)
Market share (%)	20.4	48.5

Note: The group of affected (unaffected) drugs consists of all modal packages with a price above (below) the substitution group-specific threshold for 20% coinsurance before the policy implementation. The pre-reform prices represent per-package prices (CHF) in June 2011. Recall that there are further drug groups (e.g., non-modal packages), discussed in Appendix Section 1.B, which explains why percentages do not add up to 100 percent. To calculate market shares, we use the number of claimed packages within the 12 months preceding the policy change (retrieved from claims data described in Section 1.4.1).

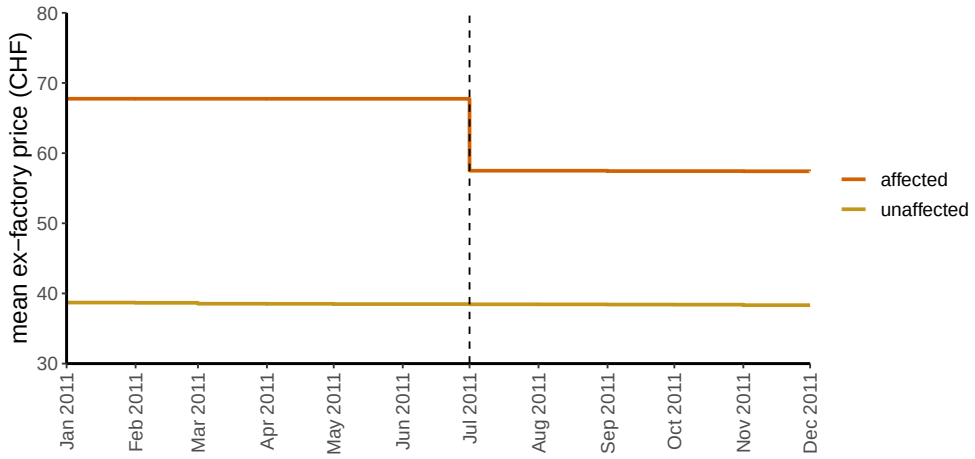
1.3.2 Measuring pharmaceutical firms' price responses

The 2011 policy change provides an ideal setup for analyzing the price responses of pharmaceutical firms. The policy may create an incentive for firms to reduce the prices of the affected products. By contrast, firms have no incentive to respond with a price change for unaffected products.[14] Moreover, there was no periodic price reassessment in July 2011, or any other event that might have led to price adjustments apart from the policy (see the timeline in Figure 1.A.1). Pharmaceutical firms generally seem reluctant to voluntarily reduce prices; in addition, price increases are almost never approved. Hence, it is very unlikely that firms change prices around July 1st, 2011 for any other reason than the incentives attributable to the policy. Indeed, Figure 1.1 shows that prices evolved horizontally without any price changes in 2011 except for July. Therefore, we apply simple before-after comparisons of pre- (June 2011) and post-reform (July 2011) prices to measure firms' price responses to the policy.

The results in Table 1.2 show that pharmaceutical firms reduce the per-package ex-factory prices of their affected products on average by CHF 10.4 (or 10.7%), which translates into an average decrease in retail prices of CHF 12.4 (or 9.86%). Whereas firms decide to reduce prices for more than 70% of the affected drugs, they do not lower prices for the unaffected drugs.

[14] As the FOPH rarely approves requests for price increases, firms cannot increase the price of low-cost drugs to the threshold. Moreover, because the threshold is based on prices in March 2011, firms in the cheapest third could not manipulate the threshold by reducing their prices after the publication of the threshold in April 2011.

Figure 1.1: Evolution of average ex-factory price



Note: The graph depicts the evolution of average ex-factory prices (per package, in CHF) for the year 2011. The "unaffected" group consists of modal packages with prices below the substitution group-specific threshold. While the "affected" group consists of all drugs that would newly be subject to 20% coinsurance as of July 1st if the pharmaceutical firms do not reduce their prices. To prevent variations in average prices due to compositional changes, we exclude drugs that enter or exit the market throughout 2011.

This finding suggests that the threat of a higher coinsurance rate provides strong incentives for firms to reduce their prices. Analyzing price responses to updated thresholds in January 2012 reveals that most firms stick to their pricing strategy.

However, firms' responses are not homogeneous. Table 1.2 indicates that the prices of most of the affected generics (83.5%) are reduced. By contrast, pharmaceutical firms are much more reluctant to lower the price of brand-name products. In fact, the probability of a price change for the affected brand-name drugs is 36 percentage points lower than that for the affected generic drugs. This observed heterogeneity may have two possible explanations. First, brand-

Table 1.2: Price reductions, July 2011

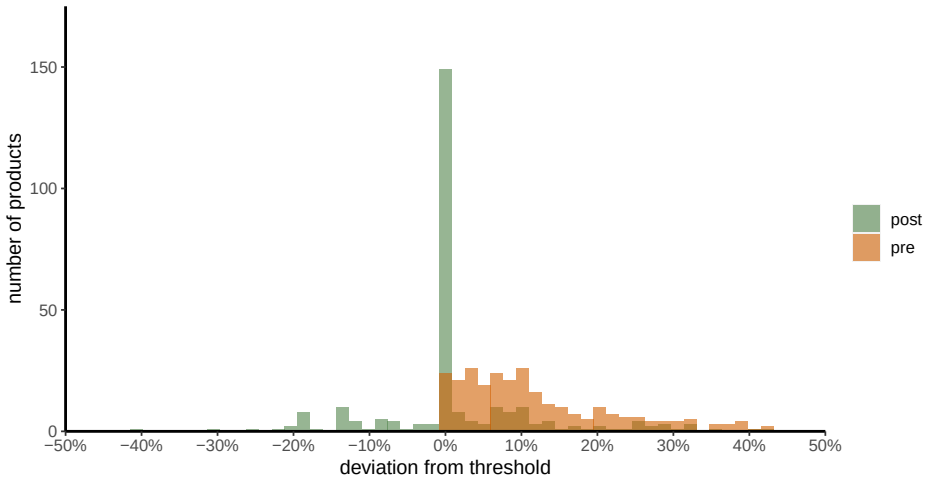
	Affected	Unaffected
Δ Ex-factory price, CHF (%)	-10.4 (-10.7)	-0.031 (-0.070)
Δ Retail price, CHF (%)	-12.4 (-9.86)	-0.035 (-0.050)
Products with price reduction, N (%)	191 (71.0)	6 (0.491)
Generics with price reduction, N (%)	147 (83.5)	2 (0.177)
Brands with price reduction, N (%)	44 (47.3)	4 (4.17)

Note: Price changes correspond to differences in post-reform (July 2011) prices compared to pre-reform (June 2011) prices. To calculate the share of generic (brand-name) products with a price decrease, the baseline is the respective numbers of affected or unaffected generic (brand-name) products.

name drugs are typically priced higher and therefore require a greater price reduction to meet the threshold. Second, producers of brand-name drugs might anticipate their patients to be less price-sensitive.

Among the firms that respond with a price decrease, the majority (76%) of firms lower their price by just enough to avoid 20% coinsurance. As illustrated in Figure 1.2, the post-reform prices of the affected drugs therefore bunch at the price threshold. However, some firms reduce their prices more than expected (24%). The main reason for this is the nonlinear structure of retail markups. Due to these nonlinearities, firms cannot set ex-factory prices to exactly meet the retail price threshold for some products (14%).[15] A further explanation for lowering prices more than required, is that some firms simultaneously reduce the prices of products with the same active ingredient but different strengths.

Figure 1.2: Pre- and post-reform deviation from 20% coins. threshold (affected products)



Note: The pre-reform deviations from the 20% coinsurance price threshold are calculated using June 2011 prices, whereas post-reform deviations are based on prices in July 2011. In this graph, the sample is restricted to affected products only.

Our results are in line with those of previous studies (see e.g., Brekke et al., 2011; Herr and Suppliet, 2017; Kaiser et al., 2014; Pavcnik, 2002). Similarly, these studies find that pharmaceutical firms' price-setting behavior is sensitive to patients' out-of-pocket payments. Moreover, results reported by Herr and Suppliet (2017) and Kaiser et al. (2014) also indicate stronger price reductions for generics. In summary, most firms decide to decrease the prices of their products to avoid 20% coinsurance. Hence, firms seem to fear loss of demand if their patients face higher out-of-pocket costs. Back-of-the-envelope calculations suggest that price reductions induced by the policy result in annual savings of CHF 19.4 Mio., which corresponds to 2.1% of spendings

[15] As described in Section 1.2.2, the threshold was calculated on retail prices until 2017, but pharmaceutical firms can only set their ex-factory price. As the retail markup increases stepwise with the ex-factory price, a decrease in the ex-factory price can lead to a greater reduction in the retail price.

on targeted drugs.[16] Moreover, the results show that brand-name producers are much more reluctant to reduce prices, suggesting that they expect their patients to be less price sensitive compared to patients purchasing generics. In the subsequent section, we investigate whether this distinct behavior of generic and brand-name firms can be justified by the varied reactions of their respective customers to higher coinsurance.

1.4 Patient demand response

Having studied the supply-side price responses of pharmaceutical firms, we now turn to analyze the potential demand-side reactions of patients to the two-tiered coinsurance policy. Specifically, we study the patients' responses to the 20% coinsurance rate for drugs for which firms decided not to reduce their prices. First, we describe the data used for the analysis. Second, we present the natural experiment utilized to estimate demand responses and outline our empirical strategy. Finally, we provide results on the causal effect of the two-tiered coinsurance policy on the probability to buy drugs subject to higher coinsurance.

1.4.1 Health insurance claims data

We use health insurance claims data to analyze the response of patients to differentiated cost-sharing. Specifically, we have access to the claims data of two large Swiss health insurers, which together covered 23.5% of the entire Swiss population in 2011. The data consists of all adults who were continuously insured from 2010 to 2012 by the same insurance company. For these individuals, we observe the canton of residence, sex, age in 5-year brackets, chosen deductible, and annual expenditures for pharmaceuticals. In addition, we have detailed information on each drug purchase. We observe the Swissmedic number, date of purchase, health care provider, and provider type (physician[17], pharmacy, or hospital), number of packages, overall costs, costs covered by health insurance, and the patient cost-sharing (deductible and coinsurance payments).

1.4.2 Price differences: a natural experiment

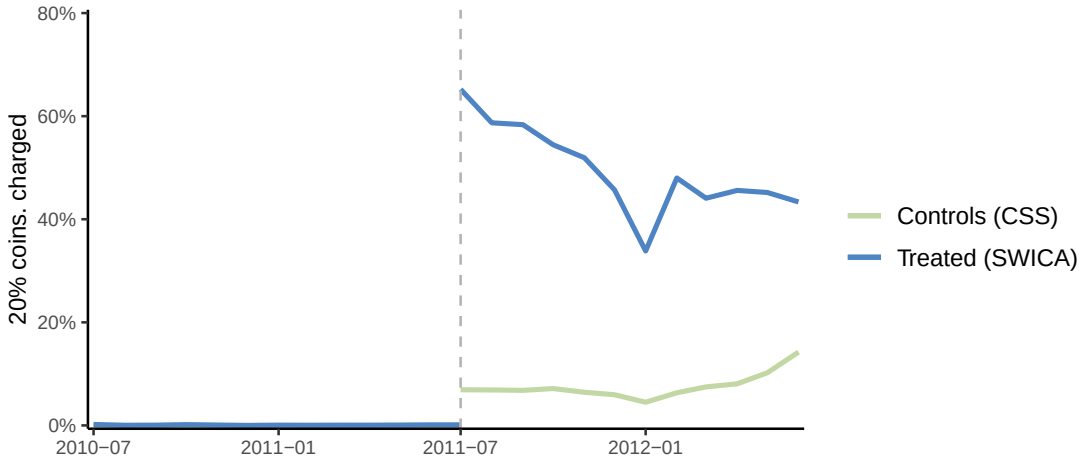
Obtaining credible estimates of the price sensitivity of the demand for prescription drugs requires an exogenous variation in prices. To this end, we exploit a computer bug that occurred

[16]The annual savings are calculated as follows: (# claimed packages July 2010 to June 2011) $\times$ (Δ prices in July 2011). The information on claimed packages is based on health insurance claims data described in Section 1.4.1. Using the market share of the data-providing health insurer in 2011, we project annual savings for all patients in Switzerland.

[17]Some Swiss cantons allow physicians to directly dispense drugs to their patients instead of writing a prescription (see e.g., Burkhard et al., 2019; Kaiser and Schmid, 2016; Müller et al., 2023; Rischatsch et al., 2013, for further information).

during claims processing in one of the two data-providing health insurers. While SWICA health insurance charged the 20% coinsurance rate as of July 2011, CSS health insurance did not correctly implement the higher coinsurance rate until August 28, 2012. For this reason, CSS patients (quasi-randomly) paid less out-of-pocket than SWICA patients for the same drugs for roughly one year. This price difference is illustrated in Figure 1.3. This figure shows the share of claims for which a higher coinsurance rate was charged among all claims for 20% coinsurance drugs.[18] In the treatment group, we observe a jump in this share from zero before the reform

Figure 1.3: The non-simultaneous implementation of 20% coinsurance



Note: The figure shows the share of claims for which the higher 20% coinsurance rate was actually charged among all claims for 20% coinsurance drugs, separately for SWICA and CSS patients and for each month in the pre-treatment and post-treatment period. The share of claims charged with 20% coinsurance does not jump to 100% for the treatment group in July 2011, because the 20% (10%) coinsurance rate does not apply to all claims even if correctly implemented (100% copayment below the deductible, 0% copayment above the stop-loss). Note that charging 20% coinsurance becomes less likely towards the end of the year (more patients have reached the stop-loss) and drops in January (most patients below the deductible) before it starts to increase again. Before the policy change, neither patients in the treatment group nor the control group were charged 20% coinsurance as the drugs considered only became subject to 20% coinsurance after July 2011.

to approximately 65% in July 2011, the first month after implementation. Recall that patients with health care expenditures below the deductible or above the stop-loss are not subject to 20% (10%) coinsurance.[19] Consequently, the 20% coinsurance rate does not apply to all claims, even if it is correctly implemented. Figure 1.3 shows that charging 20% coinsurance becomes less likely towards the end of the year when more patients have reached the stop-loss and is lowest in January when most patients are still below their deductible. On average, over the 12 months following the implementation (our observational period), 20% coinsurance was charged

[18]Note that "20% coinsurance drug" refers to drugs whose coinsurance rate increased from 10% to 20% in July 2011. We refer to these drugs with higher coinsurance after July 2011 as "20% coinsurance drugs" even in the pre-reform period, when their coinsurance rate was still 10%.
[19]100% copayment below the deductible and 0% copayment above the stop-loss

for 50% of claims among treated patients (SWICA). In contrast, in the control group (CSS), the 20% coinsurance rate was, on average, only charged for 8% of the claims. The non-zero share at CSS is most likely due to the delay between the drug purchase and the insurer's claim processing. Hence, if a drug was purchased between July 2011 and June 2012, but the corresponding claim was processed after the bug was fixed in August 2012, the 20% coinsurance was charged. Nevertheless, in the post-treatment period, the probability of being charged a higher coinsurance rate when purchasing a 20% coinsurance drug is 42 percentage points higher for SWICA patients. Overall, owing to this difference in the implementation of the 20% coinsurance rate, SWICA and CSS patients faced different out-of-pocket prices for the same drugs.

The non-simultaneous implementation of the higher coinsurance rate constitutes an ideal setup for identifying patients' demand responses in a difference-in-differences framework (see e.g., Cunningham, 2021, for details on the method). We use the 12 months before the policy change as the pre-treatment period and the 12 months afterwards as the post-treatment period to account for seasonality in health care within a year. SWICA patients are referred to as the treatment group, whereas CSS patients represent the control group. We assume that in the absence of the policy change, the probability of buying a 20% coinsurance drug would have evolved similarly for SWICA and CSS patients. Under this common trend assumption, we estimate the policy's effect on the likelihood of purchasing a 20% coinsurance drug. The standard difference-in-differences model is specified as follows,

$$y_{it} = \beta_0 + \beta_1 post_{it} + \beta_2 swica_i + \gamma \left(post_{it} \times swica_i\right) + \varepsilon_{it}, \tag{1.1}$$

where y_{it} equals one if patient i purchases a drug in claim t that becomes subject to 20% coinsurance after July 2011; $post_{it}$ indicates whether claim t belongs to the post-reform period; and $swica_i$ equals one for SWICA patients. The causal effect of interest is captured by parameter γ. It measures the demand effect of a properly implemented two-tiered coinsurance policy within a health care system that includes a deductible and a stop-loss amount. To account for potential imbalances in the observable background characteristics and pre-treatment drug demand, we apply entropy-balancing weighting based on Hainmueller (2012).[20]

A special feature of our setting, compared with previous studies (see e.g., Brekke et al., 2011; Herr and Suppliet, 2017; Kaiser et al., 2014; Pavcnik, 2002), is that it allows us to isolate the patient-driven demand effect. Providers were likely unaware that one health insurer did not charge 20% coinsurance until August 2012. Therefore, the provider-driven effect, induced by

[20]This approach reweighs control observations such that the treatment and control groups become balanced in a defined set of covariates. In our case, we use the pre-treatment drug demand measures and background characteristics, depicted in Table 1.3, for the reweighting (i.e., purchase frequency, drug costs, 20% coinsurance drug share, age, sex, deductible).

the prescription behavior of physicians and the product availability at pharmacies, is eliminated because this effect should apply to patients of both health insurers to the same extent. In the next section, we describe the data restrictions, provide summary statistics, and discuss the validity of the identifying assumptions.

1.4.3 Sample selection and descriptive statistics

In what follows, we focus on the 65 substitution groups in which at least one product switches from 10% pre-reform to 20% coinsurance after the policy change. In addition, we must consider that the CSS informed some of their patients about the possibility of using generics instead of brand-name drugs (for details, see Hjalmarsson et al., 2024). To eliminate the effect of this information, we exclude the eight substitution groups that were part of the information campaign. Furthermore, we do not observe any drug claims for ten substitution groups. Additionally, to ensure comparability, we exclude five small substitution groups for which we have observations from only one health insurer. However, this corresponds to only 0.2% of patients. This leaves us with 42 substitution groups for our analysis. Regarding patients, we focus on those for whom the policy generated an incentive to change their behavior. To do so, we restrict our sample to patients who purchased a 20% coinsurance drug at least once before the policy change, when these drugs still had a coinsurance rate of 10%. In addition, we require these patients to make at least one purchase in the same substitution group after the policy change. This ensures that we observe the same patients before and after the policy change.

In Table 1.3, we provide pre-reform descriptive statistics of the final sample, separately for the treatment and the control group. We observe total 48,093 patients across 42 distinct substitution groups. The control group is approximately 2.5 times larger than the treatment group, which reflects the difference in size between the two health insurers. The two groups are similar in terms of pre-reform drug demand and background characteristics. The pre-reform annual number of claims is approximately four in both groups, suggesting that the population considered consists primarily of chronically ill patients. Consequently, the average annual drug costs for these patients are with around CHF 2,200 fairly high. For both groups, we observe a similar proportion of drug claims that consist of 20% coinsurance drugs, which constitutes our pre-reform outcome.[21] Although the two groups appear to be similar, Table 1.3 reveals some statistically significant differences. The patients in the control group are more likely to be female, older, and to choose a low-deductible plan than the treated patients.[22] These differences might also explain the somewhat higher pre-reform drug demand in the control group. Thus, the

[21]The high share of 20% coinsurance drugs can be explained by our sample selection (only patients who at least once consumed a 20% coinsurance drug in the 12 months before the policy change).

[22]In the early 2000s, CSS offered health plans with a CHF 500 deductible that strictly dominated those with a CHF 300 deductible. Therefore, many patients chose the CHF 500 deductible, and the resulting pattern partially persisted for many years.

Table 1.3: Descriptive statistics of pre-reform outcomes and characteristics

	Treated (SWICA)	**Controls (CSS)**	**Diff.**	**P-val.**
Pre-reform drug use				
Purchase freq. (days)	165	158	7.24	0.000
Annual number of claims	3.64	3.76	-0.118	0.001
Share 20% coins. drugs	0.944	0.949	-0.005	0.005
Drug costs substitution group (CHF)	158	164	-5.405	0.010
Annual total drug costs in 2010 (CHF)	2,173	2,212	-38.9	0.321
Background characteristics				
Female	0.590	0.582	-0.008	0.103
Age group				
40^{-}	0.111	0.096	0.015	0.000
41-50	0.127	0.116	0.011	0.000
51-60	0.188	0.172	0.016	0.000
61-70	0.229	0.239	-0.010	0.016
71-80	0.222	0.247	-0.025	0.000
80^{+}	0.123	0.130	-0.008	0.019
Deductible				
300	0.758	0.714	0.044	0.000
500	0.165	0.222	-0.057	0.000
500^{+}	0.077	0.064	0.013	0.000
Number of patients	14,284	33,809		
Number of substitution groups	42	42		
Number of observations	133,281	321,847		

Note: The table presents average pre-reform drug demand per patient and substitution group for the 12 months preceding the policy implementation (July 2010 to June 2011). With the exception of the annual total drug costs in 2010, which reveal average per-patient total drug costs in 2010 (all substitution groups). The unit of observation in our estimation is a patient-claim pair.

two insurers' risk pools seem to differ slightly, which may result from patient (self-)selection into different insurers. Crucially for our identification strategy, this self-selection is independent of the differential price change caused by the billing error. Nevertheless, we use entropy-balancing weighting to control for imbalances between the treatment and control group.[23]

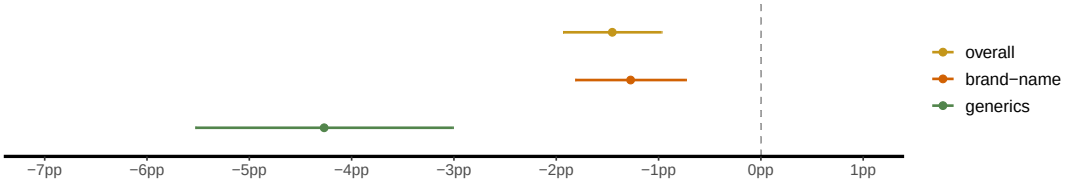
1.4.4 Demand effect estimates

Figure 1.4 depicts the result of estimating the patients' demand response which corresponds to γ in Equation (1.1). To estimate the demand response, we use OLS with entropy-balancing weights.[24] Recall that we measure the demand response by the change in the probability of buying a 20% coinsurance drug after these drugs have become subject to 20% coinsurance.

[23]Table 1.C.2 in the Appendix demonstrates that reweighting using entropy-balancing weights manages to fully balance pre-reform drug demand and background characteristics.
[24]We provide estimates without weighting in Table 1.C.3 in the Appendix.

Overall, we find a statistically significant reduction of 1.5 percentage points in the probability of buying a 20% coinsurance drug. This overall effect is close to the point estimate for brand-name drugs because, as most generic producers reduce prices to avoid 20% coinsurance, the majority of 20% coinsurance drugs in our sample are brands. By contrast, the effect for generics is almost three times larger. The probability of buying a high-priced generic drug declines by approximately 4.3 percentage points in response to the policy. These estimated effects correspond to the causal demand effects of the two-tiered coinsurance policy within a health care system including a deductible and a stop-loss amount.

Figure 1.4: Demand reactions to the policy



Note: The figure visualizes the effect of the properly implemented policy on the probability to purchase drugs with higher coinsurance ($\hat{\gamma}$), measured in percentage points (pp). The figure shows the overall and separate effect estimated for generics and brands with 20% coinsurance. The effect for generics is identified using only claims for generics, assuming that patients do not switch from generics to brand-name drugs in response to the policy. Similarly, for the brand effect, we assume that patients either stick with the 20% coinsurance brand-name drug or switch to generics with 10% coinsurance. We abstract from the possibility that they switch from a 20% coinsurance brand-name drug to a 20% coinsurance generic drug. Heteroskedasticity-robust standard errors are used to calculate the 95% confidence intervals shown in the graph.

However, on average, only approximately 50% of claims for 20% coinsurance drugs are effectively charged with the higher coinsurance rate even if correctly implemented (see Figure 1.3). This occurs because the coinsurance rate applies only if the patient has exceeded the deductible but has not yet reached the stop-loss. Therefore, if we are interested in measuring the effect of actually paying (seeing) 20% coinsurance on drug demand, we need to consider that treated patients not always pay 20% coinsurance for their purchases of 20% coinsurance drugs. To do so, we scale up the estimated (reduced-form) policy effect by the difference in the probability of being charged the 20% coinsurance rate between the treatment and the control group.[25] As stated in Section 1.4.2, patients in the treatment group are 42 percentage points more likely to be charged 20% coinsurance. We therefore divide the estimated policy effects − 1.5 percentage points for the overall market and 4.3 percentage points for generics − by 0.42. Using

[25]This is similar to the logic of instrumental variables. If we follow this logic, we would use the *swica* indicator (correctly implemented reform) to instrument the probability of actually being charged the higher coinsurance rate. Similar to the Wald estimator, we then scale up the "reduced form" effect (demand effect of correctly implemented policy) by the "first stage" (difference in the probability of being charged 20% coinsurance between treatment and control group) to obtain the causal effect of being charged a higher coinsurance rate on the probability to buy a 20% coinsurance drug.

this approach, we estimate that paying 20% coinsurance reduces demand for these drugs by approximately 3.57 percentage points. The reduction is even more pronounced for generics, with an estimated decrease in demand of 10.2 percentage points.
In summary, we find a considerably large demand response for generic drugs and a smaller demand response for brand-name drugs. These findings indicate that patients purchasing brand-name drugs are less price sensitive than patients purchasing generic drugs. This is in line with earlier findings by Herr and Suppliet (2017) and implies that substitution primarily occurs between different generics and not between brand-name and generic drugs. Both the effect of the policy itself and the effect of paying 20% coinsurance offer important insights into the benefits of out-of-pocket price differentiation and provide public health policymakers with valuable information for optimal health plan design. The next section contains a brief discussion of the results and concludes the chapter.

1.5 Discussion and conclusion

Health insurance reduces patients' exposure to the true price of health care services and goods. Therefore, they have little incentive to choose cheaper alternatives, which could lead to higher health care costs. The introduction of differences in out-of-pocket prices could improve the efficiency of the health care market. In this study, we analyze the case of higher out-of-pocket payments for expensive drugs in Switzerland. A higher 20% coinsurance rate should provide a financial incentive for patients to select cheaper drugs that are subject to 10% coinsurance only. Among patients affected by the policy, we find a small demand response for brand-name drugs and a larger response for generic drugs. Hence, patients who purchase generic drugs seem price sensitive and tend to substitute generic drugs if they face differences in out-of-pocket prices. In contrast, patients who purchase brand-name drugs tend to be less price sensitive. Our results further suggest that out-of-pocket price differentiation might be more effective in a health care system without deductible and stop-loss amount, where a constant coinsurance rate applies to all claims for prescription drugs.
While the estimated substitution in response to the policy seems modest, it would be inaccurate to consider the policy ineffective. Our study highlights that producers anticipate the demand response by reducing their prices. Overall, the policy induced an average price reduction of 11%, which translated into annual savings of roughly CHF 19.4 Mio. Without this anticipatory behavior, the demand response would likely have been more pronounced, suggesting that our demand response estimates are lower bounds. Although the policy also aimed to foster the substitution of brand-name drugs and expensive generics with cheaper alternatives, its true effectiveness is based on the interplay between price sensitive demand and profit-maximizing firms. Our results indicate that the (re)introduction of market-like mechanisms such as price

signals can be effective in enhancing health care market efficiency. Consequently, our results offer insights regarding the demand and supply of medical goods and services in a broader context. Moreover, our study provides policymakers with information on the optimal design of cost-sharing in health insurance.

Although the estimated price and demand reactions have a causal interpretation, it is important to note that these findings are not informative about the price elasticity of drug demand. First, the demand response estimates are based on drugs without price changes. If producers consider customers' price sensitivity, their decisions to change prices are endogenous. Second, our analysis primarily involves patients with chronic conditions whose price sensitivity may differ significantly from those with newly diagnosed chronic conditions or in general, individuals selecting a medication for the first time. Hence, although our estimates are helpful for understanding how the price mechanism works in the health care market, they do not provide a comprehensive view of the overall price elasticity of drug demand.

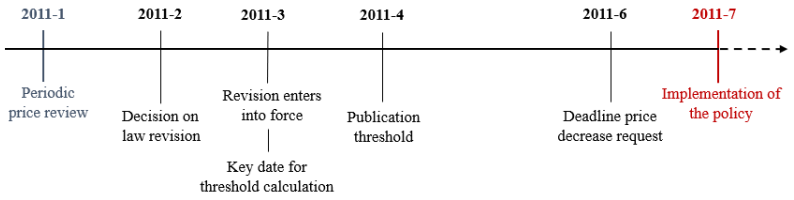
Moreover, our study adopts a short-term perspective. The policy could have long-term effects on drug supply in Switzerland, for instance, through market entry and exit decisions and the pricing strategy of newly launched products. It remains uncertain whether the 20% coinsurance policy will lead to sustained price reductions without affecting long-term drug availability. However, it is not possible to answer this question with the data at hand; and hence, it is beyond the scope of the present study. Nevertheless, answering this question is important from an overall welfare perspective and is left for future research.

1.A The two-tiered coinsurance policy

1.A.1 Detailed description of rules, exemptions, and implementation timeline

Figure 1.A.1 provides an overview of the policy implementation in 2011. The decision to adopt the new policy was made in February. In March, the policy entered into force and March prices were used to define the substitution group-specific price thresholds. The calculated thresholds were published in April together with the information whether products would be subject to 20% coinsurance after July 2011 if prices were not reduced. Firms had the possibility to file a price decrease request until end of June to avoid the higher coinsurance on their affected products. In July 2011, the policy was implemented, meaning that all drugs in the targeted substitution group (at least three therapeutically equivalent drugs) with a modal package price above the substitution group-specific threshold were charged with 20% coinsurance.

Figure 1.A.1: The 20% coinsurance implementation in 2011



Note: The graph shows the implementation of the two-tiered coinsurance policy in 2011. The decision to adopt the policy occurred in February 2011 and it was enacted in March. The Federal Office of Public Health published the thresholds in April, which allowed firms to file a price decrease request until June. If a firm decided not to decrease the price for drugs above the substitution group-specific threshold, these drugs became subject to 20% coinsurance as of July 1st, 2011. Additionally, in January 2011, there was a periodic price review for brands (and their generic versions) added to the specialities list before 2006. The next periodic price review was in November 2011, however, only for brands (and their generic versions) listed since 2008.

Table 1.A.1 provides details on the two-tiered coinsurance policy, its objectives, rules and exemptions. The policy was implemented to incentivize the substitution of expensive brand-name and generic drugs with its cheaper alternatives and to induce price reductions by pharmaceutical firms. The policy only targeted substitution groups with at least three therapeutically equivalent drugs to ensure that patients have the option of switching to products with regular coinsurance of 10%. Recall that a substitution group refers to drugs with the same active ingredient, strength, and galenic form. In 2011, the FOPH defined the price threshold, above which drugs were threatened with higher coinsurance, as the average retail price of the cheapest third within the substitution group scaled up by 20%.[26] Since 2017, the threshold is based on

[26]For instance, for substitution groups with three or four drugs, the cheapest third consists of the cheapest drug. For substitution groups with five to seven drugs, the cheapest third consists of the two cheapest drugs.

ex-factory prices rather than retail prices and the scaling factor is reduced from 1.2 to 1.1. As per-unit prices vary by package size, the best-selling package (modal package) is used to determine the threshold and to identify affected drugs. A modal package is affected if its retail price is above the substitution group-specific threshold for the 20% coinsurance rate. If producers of affected drugs decide not to reduce the price of the modal package, all package sizes of the corresponding drug become subject to 20% coinsurance after the policy implementation in July 2011. Note that since 2017, producers have to reduce the prices of all package sizes accordingly to avoid higher coinsurance. Brand-name drugs can be exempted from the policy for a period of 24 months, if their prices are reduced to the generics level at patent expiry. For a more detailed description of the categories of drugs differently impacted by the policy, we refer to Table 1.B.1. In the next paragraph, we illustrate the two-tiered coinsurance policy using the specific example of simvastatinum to further enhance understanding of the policy.

Table 1.A.1: Two-tiered coinsurance policy, July 2011

Objectives	• Substitution of expensive drugs with cheaper alternatives • Price reductions of pharmaceutical firms
Criteria for reform inclusion	Substitution group* with at least three therapeutically equivalent products *Drugs with same active ingredient, strength, and galenic form
Substitution group-spec. threshold	∅ retail price of cheapest third +20% (2011-2016) ∅ ex-factory price of cheapest third +10% (since 2017)
Modal package	• Best-selling package size within past 12 months • Relevant package size for threshold calculation and identification of affected products
Affected	Modal package with price *above* threshold in April 2011
Unaffected	Modal package with price *below* threshold in April 2011
Pharmaceutical firms' options	• Reduce product price before July 2011 to threshold to avoid 20% coinsurance (only reduction of modal-package price required until 2017) • No price change → accept higher coins. on all packages sizes
Exemptions	• Brands for which price was reduced to generic price level at patent expiry (exempted for 24 months)

Note: The table presents an overview of the two-tiered coinsurance policy. The policy applies to substitution groups with at least three therapeutically equivalent products. The modal package prices of the cheapest third within a substitution group are used to calculate the substitution group-specific price threshold. If the modal package price is above this threshold, and the modal package price is not reduced before July 2011, all package sizes of this drug become subject to 20% coinsurance (instead of 10%) after July 2011. The policy was adapted in 2017: Since then, firms have to reduce the prices of all package sizes to avoid 20% coinsurance and the threshold is calculated based on ex-factory rather than retail prices.

1.A.2 Example simvastatinum

Figure 1.A.2 illustrates the threshold calculation and the identification of affected products at the example of simvastatinum, a statin used to treat high cholesterol. The graph plots the per-unit prices for packages with 100 pills (modal package) from various producers. This substitution group consisted of 9 generics and 1 brand-name drug in March 2011. In this case, the cheapest third included 3 products (simvastatin actavis, simvastatin streuli, and simvastatin teva). The threshold was thus calculated as the weighted average of the per-pill prices of these three modal packages scaled by 1.2:

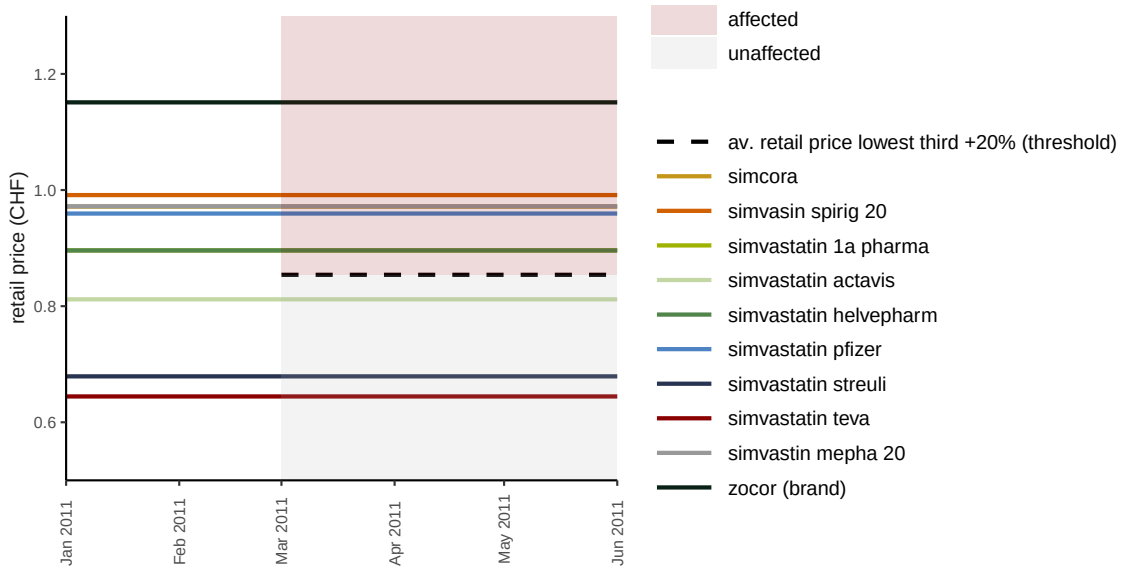
$$\text{threshold (in CHF)} = \frac{0.811735 + 0.679082 + 0.644500}{3} \times 1.2 = 0.71177 \times 1.2 = 0.85412$$

At the time of the publication of this threshold in April 2011, 7 modal packages had a price above the threshold and were therefore *affected* by the policy (i.e., threatened to be charged with higher coinsurance starting from July 2011). The three drugs with modal package prices below the threshold were *unaffected* by the policy change in July 2011, meaning that they had no incentive to reduce prices. Note that price increases are almost never approved by the FOPH, which is why firms could not increase prices for below-threshold drugs. Figure 1.A.3 further reveals that five affected generic producers reduced the price of the modal package to the threshold in July 2011 to avoid 20% coinsurance on their products, whereas one generic and the brand-name producer did not change their prices. Consequently, *simvastatin 1a pharma* and *zocor* became subject to 20% coinsurance after July 2011.

Using the example of simvastatinum, we can illustrate that the two-tiered coinsurance rate manages to introduce stronger differences in out-of-pocket prices between more and less expensive drugs. For instance, before the policy change, the brand-name modal package (zocor, 100 pills), cost CHF 115, resulting in out-of-pocket costs of CHF 11.50 (10% coinsurance).[27] After the policy change, the out-of-pocket costs double for this drug (20% coinsurance). The patient therefore pays CHF 23.00 out-of-pocket per package. In contrast, for a (fictive) product with a price equal to the threshold, the patient pays CHF 8.54 out-of-pocket before and after the policy change. Hence, the difference in out-of-pocket costs for the brand-name drug and the cheaper alternative is fairly small before the reform (CHF 11.50 vs. CHF 8.54), whereas the patient has considerably higher out-of-pocket costs for the brand-name drug after the policy implementation (CHF 23.00 vs. CHF 8.54). Thus, the policy change succeeds in increasing the out-of-pocket price differences between expensive drugs and their cheaper alternatives.

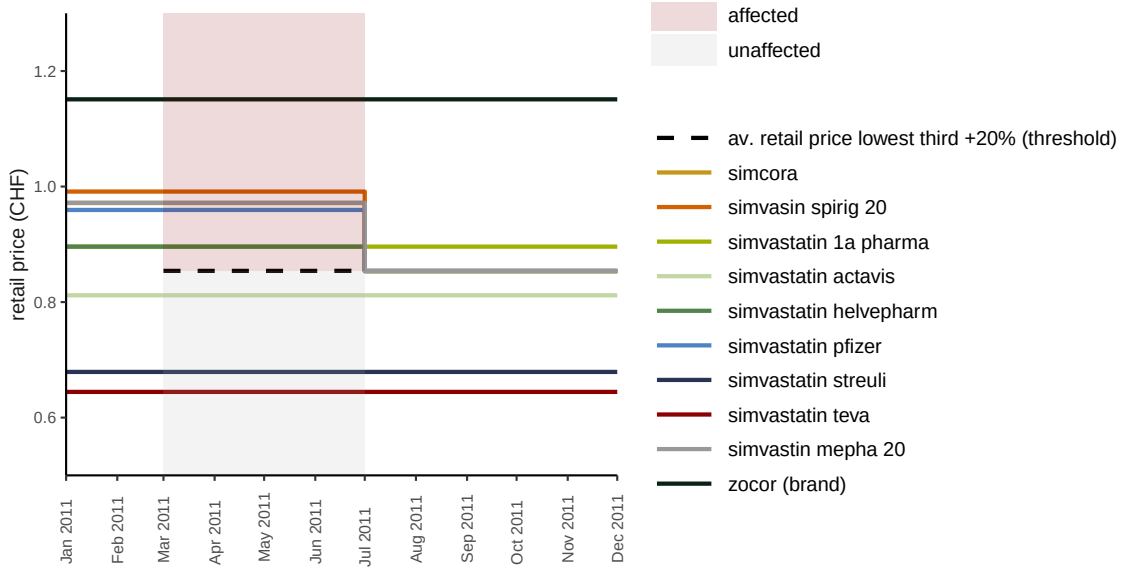
[27] Note that out-of-pocket costs are calculated for patients above the deductible and below the stop-loss at the time of purchase.

Figure 1.A.2: Example: simvastatinum, oral, 20mg



Note: The figure demonstrates the calculation of the price threshold for the 20% coinsurance rate based on prices in March 2011 and the identification of drugs affected by the reform (all drugs with retail price above the threshold) at the example of simvastatinum. Simvastatinum is a statin used to treat high cholesterol. The prices represent prices per drug unit / pill. Because some producers charge (almost) the same per-unit retail prices, some lines in the graph overlap: Simvastatin produced by helvepharm and 1a pharma, and simvastatin by mepha and simcora had the same per-unit retail price between January 2011 and June 2011, respectively. The price threshold was implemented in July 2011 (see Figure 1.A.3 for the firms' price responses in July).

Figure 1.A.3: Example: simvastatinum, oral, 20mg (price responses)



Note: The figure depicts the firm's price responses to the 20% coinsurance policy for oral simvastatinum drugs (20mg) in July 2011. As of July 1st 2011, most generic firms reduced the ex-factory price of their affected modal package to exactly meet the retail price threshold and thus avoid the higher coinsurance on their products. Because some producers charge (almost) the same per-unit retail prices, some lines in the graph overlap: Simvastatin produced by helvepharm and 1a pharma, and simvastatin by mepha and simcora had the same per-unit retail price between January 2011 and June 2011, respectively. Moreover, post-reform prices of simvasin spirig, simvastatin helvepharm, simvastatin pfizer, simvastatin mepha, and simcora equal the threshold price.

1.B Price development for various product groups

This section provides information on the price development of products differently impacted by the policy change in July 2011. In addition to the two groups of affected and unaffected modal packages, discussed in the main part of the paper, we show descriptive statistics on pre-reform prices and (the absence of) price responses for non-modal packages, exempted drugs and drugs subject to 20% coinsurance before July 2011. The six distinct groups of products are described in more detail in Table 1.B.1.

Table 1.B.1: Product groups differently impacted by the 2011 policy change

Group	**Description**
Affected	Modal packages with price above the substitution group-specific threshold for the 20% coinsurance rate.
Unaffected	Modal packages with price below the substitution group-specific threshold for the 20% coinsurance rate.
Not modal (modal affected)	Non-modal packages with corresponding modal package with price above the substitution group-specific threshold for the 20% coinsurance rate.
Not modal (modal unaffected)	Non-modal package with corresponding modal package with price below the substitution group-specific threshold for the 20% coinsurance rate.
Exempted	Brand-name drug with price reduction to generics level at patent expiry such that exempted from the two-tiered coinsurance policy for a period of 24 months.
Coins. 20 before	Brand-name drugs that were subject to 20% coinsurance before July 2011 due to an earlier policy introduced in 2006. For these drugs, the 2011 policy does not represent a change because firms have decided to accept higher coinsurance on these drugs in the past. Still it might have a reminder effect or the required price reduction to meet the threshold might have changed over time due to regular price reviews, altering the basis for decision-making.

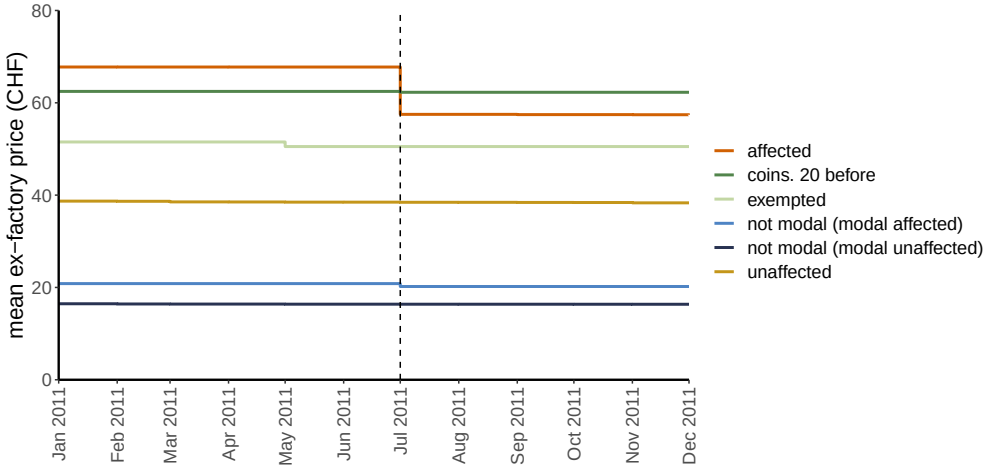
Note: The table presents and describes the six distinct groups of products differently impacted by the two-tiered policy introduced in July 2011.

Figure 1.B.1 shows the evolution of average ex-factory prices by product group. Similar to the affected and unaffected drugs, apart from July, there are essentially no price adjustments for the other four groups in 2011.

As discussed in the main part of the paper, we observe a considerable reduction in average ex-factory prices for affected drugs in July 2011, while firms do not reduce prices for unaffected drugs. Table 1.B.2, Panel B, further demonstrates that there is likewise no price change for below-threshold drugs with non-modal package size and exempted drugs. Interestingly, some firms reduce prices of non-modal packages with corresponding affected modal package, which could indicate that those firms did not fully understand the policy. Moreover, firms reduced prices for 13% of drugs subject to 20% coinsurance pre-reform. However, the decrease in

average prices for these drugs is negligible. Note that this product group consists exclusively of brand-name drugs and had the highest average pre-reform prices.

Figure 1.B.1: Evolution of average ex-factory price (all product groups)



Note: The figure shows the evolution of average ex-factory prices (per package, in CHF) for 2011 by drug group differently impacted by the policy change in July 2011 (see Table 1.B.1). To prevent variations in average prices due to compositional changes, we excluded drugs that entered or exited the market throughout 2011.

Table 1.B.2: Pre-reform prices / market shares and price responses in July 2011

	Affected	Unaffected	Not modal (modal aff.)	Not modal (modal unaff.)	Exempted	Coins. 20 before
A. Pre-reform descriptive statistics						
Number of products, N (%)	269 (8.71)	1221 (39.6)	309 (10.0)	1,206 (39.1)	58 (1.88)	23 (0.745)
Number of generics, N (%)	176 (6.63)	1125 (42.4)	218 (8.22)	1,133 (42.7)	0 (0.000)	0 (0.000)
Number of brands, N (%)	93 (21.4)	96 (22.1)	91 (21.0)	73 (16.8)	58 (13.4)	23 (5.30)
Mean ex-factory price (CHF)	70.11	38.77	20.73	16.99	50.52	62.47
Mean retail price (CHF)	95.22	58.03	35.79	30.29	72.62	87.04
Market share (packages) (%)	20.4	48.5	5.60	17.9	5.55	2.10
Market share (revenue) (%)	25.4	46.9	3.72	9.62	10.6	3.81
Generics share (%)	65.4	92.1	70.6	94.0	0.000	0.000
B. Price reductions in July 2011						
Δ Ex-factory price, CHF	-10.4	-0.031	-0.608	-0.007	0.000	-0.192
Δ Ex-factory price (%)	-10.7	-0.070	-3.84	-0.030	0.000	-0.860
Δ Retail price, CHF	-12.4	-0.035	-0.988	-0.011	0.000	-0.398
Δ Retail price (%)	-9.86	-0.050	-3.24	-0.030	0.000	-1.21
Products with price red., N (%)	191 (71.0)	6 (0.491)	44 (14.2)	3 (0.249)	0 (0.000)	3 (13.0)
Generics with price red., N (%)	147 (83.5)	2 (0.178)	29 (13.3)	2 (0.177)	-	-
Brands with price red., N (%)	44 (47.3)	4 (4.17)	15 (16.5)	1 (1.37)	0 (0.000)	3 (13.0)

Note: Pre-reform market shares in Panel A are based on packages sold and revenue (using health insurance claims data described in Section 1.4.1) in the period from 2010-07 to 2011-06. Pre-reform prices represent per-package prices (in CHF) in June 2011. Price reductions are calculated comparing post-reform prices (July 2011) to pre-reform prices (June 2011). The relative frequencies of generics (brands) in a group are calculated as the number of generics (brands) in the group divided by the total number of generics across all targeted substitution groups. In contrast, the generics share represents the share of generics within a product group in total number of products within this group.

1.C Additional tables

Table 1.C.1: Distribution markups

Ex-factory price, CHF	Markup, percent price dependent	Markup, CHF per package	Retail price, CHF excl. VAT
0.05 - 4.99	12.0%	4.00	4.06 - 9.59
5.00 - 10.99	12.0%	8.00	13.60 - 20.31
11.00 - 14.99	12.0%	12.00	24.32 - 28.79
15.00 - 879.99	12.0%	16.00	32.80 - 1,001.59
880.00 - 2,569.99	7.0%	60.00	1,001.60 - 2,809.89
> 2,570.00	0.0%	240.00	>2810.00

Note: The retail price of prescription drugs in Switzerland consists of the ex-factory price and two distribution markups. The Federal Office of Public Health determines the ex-factory price and specifies the distribution markups in a bylaw (the Table here is based on art. 35a KLV). Note that these distribution markups have not changed since 2009.

Table 1.C.2: Descriptive statistics of pre-reform outcomes and characteristics (weighted)

	Treated (SWICA)	**Controls (CSS)**	**Diff.**	**P-val.**
Pre-reform drug demand				
Purchase freq. (days)	96.4	96.4	-0.036	0.972
Share 20% coins. drugs	0.909	0.908	0.001	0.886
Drug costs substitution group (CHF)	270	267	2.32	0.767
Annual drug costs in 2010 (CHF)	2,719	2,698	21.3	0.767
Background characteristics				
Female	0.592	0.592	0.001	0.921
Age group				
40^{-}	0.111	0.109	0.002	0.741
41-50	0.124	0.124	0.001	0.925
51-60	0.174	0.174	0.000	0.931
61-70	0.223	0.223	0.000	1.000
71-80	0.227	0.230	-0.003	0.591
80^{+}	0.141	0.141	0.000	0.956
Deductible				
300	0.790	0.793	-0.002	0.672
500	0.150	0.148	0.002	0.668
500^{+}	0.060	0.060	0.000	0.925
Number of patients	14,284	33,809		
Number of substitution groups	42	42		
Number of observations	133,281	321,847		

Note: The numbers represent weighted averages using entropy balancing weights and controlling for the per-patient number of pre-treatment claims to ensure a balanced estimation sample where our observational unit is a claim-patient pair. For the entropy-balancing weighting, we used the pre-reform drug demand measures and background characteristics listed in this table.

Table 1.C.3: Demand effects of the policy

	Panel A: Weighted			*Panel B:* Unweighted		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	0.9089	0.7493	0.9080	0.9260	0.7954	0.9229
	(0.0009)	(0.0026)	(0.0010)	(0.0007)	(0.0021)	(0.0008)
post	-0.0707	-0.1174	-0.0679	-0.0716	-0.1333	-0.0685
	(0.0014)	(0.0037)	(0.0016)	(0.0012)	(0.0032)	(0.0014)
swica	-7.62×10^{-14}	-0.0033	2.21×10^{-5}	-0.0171	-0.0493	-0.0149
	(0.0015)	(0.0044)	(0.0017)	(0.0014)	(0.0042)	(0.0016)
post × swica	-0.0145	-0.0427	-0.0127	-0.0136	-0.0268	-0.0121
	(0.0025)	(0.0064)	(0.0028)	(0.0024)	(0.0062)	(0.0027)
Observations	378,990	104,067	295,883	378,990	104,067	295,883

Note: Heteroskedasticity-robust standard-errors in parentheses. The probability to buy a 20% coinsurance drug is the dependent variable. Panel (A) presents the coefficients estimates from Model (1.1) defined in Section 1.4.3 applying entropy-balancing weighting. Panel B shows the unweighted estimation results. The first column in each panel (Columns (1) and (4)), shows the overall effect. The second column in each panel ((2) and (5)) presents the effect of the policy on generics and the last column in each panel ((3) and (6)) the effect on brands with higher coinsurance.

Chapter 2

Forward-looking behavior in health insurance

joint with Caroline Chuard and Christian Schmid

Abstract

We investigate whether individuals adjust their health care utilization in anticipation of forthcoming price changes. Leveraging an exogenous increase in cost-sharing in the Swiss health care system at the age of 18, we estimate the impact of future price changes on current health care demand. Results indicate that individuals expecting higher future prices augment current outpatient health care spending by approximately CHF 39.7 (or 4.8%). This behavior is confined to low-cost male individuals, who likely have the strongest incentives to engage in anticipatory spending. We find no evidence for forward-looking behavior in the inpatient sector. Our study underscores the significance of forward-looking behavior in health care demand analysis, health insurance design, and the potential welfare implications of patient cost-sharing.

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2.1 Introduction

Health insurance involves a fundamental welfare trade-off between the gain from risk protection and the loss from moral hazard (see e.g., Arrow, 1963; Cutler and Zeckhauser, 2000). To mitigate the patients' incentive to demand unnecessary health care, the optimal health insurance contract should incorporate patient cost-sharing (Ellis and Manning, 2007; Ellis et al., 2015; Goldman and Philipson, 2007). This cost-sharing should ideally be time-invariant but vary according to the health benefits of the treatment. In practice, patient cost-sharing is less complex and most health care systems use a combination of (annual) deductibles and coinsurance with (an annual) stop-loss. This creates, however, non-linear price variations over time, which imply that the patients' out-of-pocket "spot price" can differ from the future price. If individuals consider future prices in their decision-making, they are referred to as being forward-looking. Forward-looking behaviour could impact the effectiveness of patient cost-sharing and in turn have implications for the optimal design of health insurance plans.

To analyse whether individuals are forward-looking, we exploit the exogenous increase in patient cost-sharing (deductible and stop-loss amount) in Switzerland in the year after children have reached adulthood. Our approach leverages two distinct features within the Swiss health insurance system. Firstly, individuals can select their deductible levels, ranging from CHF 0 to CHF 600 for children and from CHF 300 to CHF 2500 for adults. Upon reaching their deductible, they encounter a coinsurance rate of 10 percent and a stop-loss amount of CHF 350 for children and CHF 700 for adults. Consequently, individuals experience an increase in the out-of-pocket price upon transitioning from the child to the adult health plan. Secondly, the deductible escalates at the onset of the next year after individuals attained adult status, in the Swiss case at age 18. This creates a distinct discontinuity at the turn of the year. For instance, an individual who turns 18 on December 31 transitions into the adult scheme in January of the following year, while someone who turns 18 on January 1 remains within the child health plan for an additional year, despite their age difference being only one day. Thus, during the current year, both individuals face identical prices, yet they hold differing forward-looking price perspectives.

We use data from CSS insurance, Switzerland's largest mandatory health insurer, which encompasses approximately one-sixth of the Swiss population. Our study covers the period from 2010 to 2020 and targets birth cohorts spanning from 1993 to 2001, capturing individuals aged 16 to 20. Focusing on these cohorts allows us to investigate the transition from adolescence to adulthood and its subsequent years. The data comprises demographic information, health plan particulars, and health care claims. Our analysis is centered on diverse health care demand measures, including overall health care expenditures, visits, laboratory services and drug purchases.

Our results provide evidence for forward-looking behavior. Individuals increase their health care demand in the year preceding the exogenous increase in the out-of-pocket price. The estimated effect on physician visits and outpatient costs is mainly driven by male individuals, who constitute the subgroup with on average lower health care costs pre-treatment. Based on descriptive evidence, this subgroup has the strongest incentives to increase their health care consumption in the last year with the lower cost-sharing for several reasons. Most importantly, low-cost males experience a higher increase in cost-sharing as they generally choose a higher deductible when entering the adult health plan. Our findings additionally suggest that the increased health care demand among male individuals in the last year before the out-to-pocket price increase, is rather extra demand than demand shifting across periods.

Our results contribute to an expanding body of literature indicating that individuals exhibit forward-looking behavior in response to non-linearities. There are two strands of literature focusing on different types of forward-looking behavior. One strand studies, as we do in our paper, whether individuals are optimizing health care demand across years, when there is a definite and salient change in out-of-pocket prices at the turn of the year (e.g., deductible or stop-loss reset). For instance, Brot-Goldberg et al. (2017) find clear evidence of excess spending in the last quarter of the year before an exogenous shift from a free-care health plan to a high-deductible plan. The spending increases among employees affected by the change in the firms' health plan options are estimated to be approximately 2.6% to 5%, similar in magnitude to this study's estimates. Moreover, Gerfin et al. (2015) study how patients who have hit their deductible in a given year respond to the discrete jump in the spot price at the turn of the year when the deductible resets. Their results suggest that health care demand drops by 27% for individuals with high deductibles, whereas individuals with low deductibles do not significantly change their health care demand. Consistent with our findings, they provide evidence that forward-looking behavior is more pronounced among healthier individuals with on average greater changes in future prices.[1] Furthermore, Lin and Sacks's (2019) findings on demand increases in response to future price increases are also in line with our study. They use data from the RAND Health Insurance Experiment and find that hitting the stop-loss, such that the out-of-pocket price for health care is temporary at zero, leads to a considerable increase in health care demand anticipating higher future (out-of-pocket) prices. They further find that such short-lasting price changes cause stronger demand responses compared to long-lasting price changes (e.g., free-care health plans). Finally, they find evidence for demand shifting across periods. In contrast, we find no clear evidence for demand shifting in our sample of young and relatively healthy individuals. Rather, we find a slight increase in health care demand in the last year with lower out-of-pocket prices with no corresponding decrease in health care demand

[1] Gerfin et al. (2015) refer to low-cost individuals as healthy individuals, abstracting from the possibility that low-cost individuals are not necessarily healthy but might underuse health care.

in the first year with higher out-of-pocket prices.

Closely related but with reversed incentives, several studies found demand reductions in response to lower future prices. While Cabral (2016) demonstrates that patients delay dental treatments when anticipating price decreases in subsequent years, Alpert (2016) shows that individuals reduce claims for chronic drugs anticipating the implementation of Medicare Part D, which covers prescription drugs. Similarly, Einav et al. (2015) find evidence for delaying drug purchases if individuals covered by Medicare Part D are in the "donut hole" at the end of the year.[2] Furthermore, Johansson et al.'s (2023) results for Sweden indicate that elderly individuals engage in forward-looking moral hazard by delaying primary care visits to benefit from the elimination of out-of-pocket costs for primary care upon turning 85 years old.

The second strand of literature on forward-looking behavior, more loosely related to our study, examines whether individuals adapt their health care demand in anticipation of expected end-of-year prices. Most studies find that individuals are rather myopic in this regard, hardly reacting to expected end-of-year prices (see e.g., Aron-Dine et al., 2015; Brot-Goldberg et al., 2017). Hence, individuals seem to be forward-looking around the coverage reset − studied in this paper − but spot-price biased for health care demand throughout the year.[3]

The majority of existing literature focuses primarily on the elderly population or individuals with chronic illnesses (see e.g., Alpert, 2016; Einav et al., 2015; Johansson et al., 2023). Others study employer-based health insurance for well-educated and relatively high income employees (Brot-Goldberg et al., 2017) or use data from the RAND Health Insurance experiment conducted many years ago (Lin and Sacks, 2019). Moreover, where most studies concentrate on some specific outcomes, such as the demand for prescription drugs (see e.g., Alpert, 2016; Einav et al., 2015; Hjalmarsson, 2024), dental treatments (Cabral, 2016) or primary care visits (Johansson et al., 2023), we study a broad set of different health care demand measures. Hence, our contribution to this body of research lies in examining the impact of an exogenous out-of-pocket price increase in the subsequent year on current health care demand among the young using a very recent observational period. This part of the population is typically characterized by relatively good health, potentially limiting their opportunities for timing health care consumption. By investigating forward-looking behavior for this specific group and for a broad set of health demand measures, our findings offer valuable insights into how annual deductibles and copayments influence individual health care demand.

The remainder of the chapter is organized as follows: Section 2.2 explains the institutional

[2]Upon reaching their deductible, individuals covered by Medicare Part D only pay 25% of further expenditures for prescription drugs. However, if their expenditures exceed some predefined amount, individuals enter the so-called donut hole and again pay the full price for prescription drugs out-of-pocket until reaching the stop-loss (see e.g., Einav et al., 2015, for details).

[3]Simonsen et al. (2021) state that those, at first sight, contradicting findings both can be explained by spot price bias. They suggest to interpret changes in health care demand due to a coverage reset as large and salient differences in spot prices between the last day before and the first day after the turn of the year.

setting including the transition from the child to the adult health plan, as later used for causal identification. Sections 2.3 and 2.4 explain the data and the empirical framework. We study forward-looking behavior and explain possible drivers for the documented results in Section 2.5. While our data structure allows to follow an individual over several years, we also explore the implications of forward-looking behavior in one year on health care consumption in the next year, as shown in Section 2.6. Finally, we conclude in Section 2.7.

2.2 Institutional setting

Similar to the health care systems in the Netherlands, in Germany, and under the Affordable Care Act in the United States, health insurance in Switzerland is characterized by competitive elements as well as strong governmental regulations (the description hereafter draws on Schmid et al., 2018). Individuals can freely choose among more than 50 private insurers that compete on price and quality, but health plans are subject to strong regulation ensuring risk solidarity, affordability, and access to health care. All insurers must offer the standard health plan, which includes free physician choice, an individual deductible of CHF 300, and a coinsurance rate of 10% up to the stop-loss amount of CHF 700. Besides this standard health plan, individuals can opt for higher deductibles ranging from CHF 500 to CHF 2,500 (see Table 2.1, column 2). Moreover, individuals can choose managed-care health plans including telemedicine, preferred provider, and health maintenance organization plans. These plans restrict direct access to specialists in contrast to free physician choice in the standard health plan. Patients in managed-care plans are required to first contact their general practitioner (GP) or a telemedicine provider, who act as gatekeepers. Besides differences in gatekeeping and deductible amount, every health plan has to offer the same predefined coverage in terms of services. Choosing a health plan with a higher deductible and/or managed-care features results in a lower premium.[4]

Table 2.1: Cost-sharing in children and adult health plans

	Child health plan (0-18y)	Adult health plan (> 18y)
Standard deductible (in CHF)	0	300
Deductible options (in CHF)	100, 200, 300, 400, 500, 600	500, 1000, 1500, 2000, 2500
Stop-loss (in CHF)	350	700

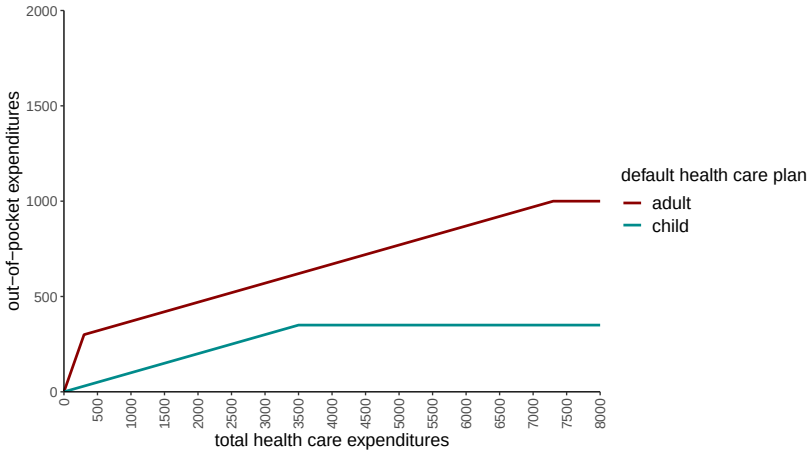
Note: This table displays the standard deductible, the deductible options and the stop-loss amount in the child and the adult health plan. Individuals are in the child health plan as long as they are aged below 18 years and transition to the adult health plan in the year after they have turned 18 years old.

[4]Furthermore, individuals get a premium discount if they opt to suspend their accident coverage. This becomes feasible when an individual is employed for at least eight hours per week, at which point their employer is obligated to provide accident coverage.

Crucial for our research question at hand, protecting child health is regarded more important than mitigating moral hazard. Therefore, patient cost-sharing for children is reduced (see Table 2.1, column 1). First, the individual deductible in the standard health plan is zero and the stop-loss amount for the 10% coinsurance is lowered to CHF 350.[5] Second, the voluntary deductibles range from CHF 100 to CHF 600. Moreover, to limit the financial burden on families, the child premium is about a quarter of the adult premium.[6] Apart from the lower premium and the reduced patient cost-sharing, health plan choices for children and adults are the same. In particular, children can also enroll into managed-care health plans.[7]

The transition from the child health plan to the adult health plan occurs at the onset of the year during which individuals turn 19. For instance, individuals celebrating their 18th birthday on December 31 are adult in the following year, whereas their peers turning 18 on the next day, that is, January 1, are still considered children for the entire year (from a health insurance perspective). This holds significant implications, as individuals born within days of each other may encounter vastly different future prices. Because of the change in the deductible set and the increase of the stop-loss amount when turning adult, adults usually pay more out-of-pocket for the same health care service than children. Figure 2.1 demonstrates this difference in

Figure 2.1: Cost-sharing in the default child and adult health plan



Note: The graph reveals the differences in out-of-pocket expenditures between individuals in the default child health plan and the default adult health plan for different levels of total health care expenditures. The default deductible is CHF 0 for children and CHF 300 for adults. Below the deductible, individuals pay their health care costs fully out-of-pocket. After reaching the deductible, individuals pay a coinsurance of 10% up to a stop-loss amount. The stop-loss amount for adults (CHF 700) is twice the stop-loss for children (CHF 350). There is no patient cost-sharing above the stop-loss.

[5]If a family has more than two children insured with the same insurer, the children's cumulative stop-loss amount is CHF 700.

[6]Note that health insurers can grant a premium discount to "young" adults aged 19 to 25, which they usually do. The child premium is hence roughly one third of the young adult premium.

[7]Some health insurers require a minimum age of to enroll in certain managed-care health plans (e.g., 12 years for the telemedicine plan).

out-of-pocket costs between children and adults in their corresponding standard health plan for different levels of total annual health care expenditures. Consequently, despite being of the same age and having the same out-of-pocket price during the last year in which both, individuals born before and after the turn of the year, are still in the child health plan, the two groups diverge substantially in the future price for health care. Leveraging the similarity between these two groups allows us to estimate the effect of a future price change on current demand. The empirical strategy is described in more detail in Section 2.4.

For the interpretation of our results, it is important to understand how and when individuals are informed about their transition to the adult health plan. First, individuals born in December receive a letter in April of the year in which they turn 18 and are asked to redefine the contact person for their premium bills, benefit statements and further correspondence. Up to this point, the parents have usually been recorded as contact person(s).[8] This letter, however, does not contain any specific information on the transition to the adult health plan in the following year. Between April and October, the responsible client advisor informs the children (or their parents) about next year's premium increase associated with their transition to the adult health plan.[9] In October, the health insurance company sends out the new insurance policy revealing next year's monthly insurance premium for the chosen deductible, or the default deductible plan if no voluntarily deductible was specified. Therefore, at the latest in October, individuals should be aware of their transition into the adult health plan with higher insurance premium and higher cost-sharing.

2.3 Data

2.3.1 Health insurance claims data

For our analysis, we rely on data from CSS insurance, Switzerland's largest mandatory health insurer. CSS covers approximately 1.5 million clients, which accounts for about one-sixth of the Swiss population. We use outcome data for the years 2010−2020 and focus on birth cohorts 1993−2001, encompassing by health plan definition *children* aged 16 to *adults* aged 20. This approach allows us to examine two years preceding adulthood and the two subsequent years after transitioning. For each individual in our data, we observe the health plan including managed care features, the deductible, whether accident coverage is included, and the premium. Moreover, we observe the invoice address which provides information on whether the individuals

[8] Based on our data, even after turning 18 years, most individuals ($\sim$ 99%) keep their parents as contact persons, either deliberately or because they do not reply to the letter.

[9] In this phone call, individuals are additionally informed about their possibility of suspending accident coverage if they are in paid employment. As this could affect observed accident-related health care costs, we focus on illness-related costs in this study.

or their parents receive the (premium) bills.[10] In terms of background characteristics, we have information on the date of birth, sex, language, nationality and canton of residence.
Turning to health care demand, our data includes detailed information on the individuals' interactions with the health care sector. Specifically, we observe for each health insurance claim the date of provision, the gross costs and the patient cost-sharing, and the cost category (inpatient, outpatient, prescriptions, laboratory services). While outpatient diagnosis are generally not observed, we have information on 26 chronic diseases based on drug usage (so-called "pharmaceutical cost groups"). Furthermore, with provider information linked to each claim, we can identify provider specialization. Based on this rich data, we focus on various health demand measures derived from the combination of health care claims and provider data. These measures include overall gross health care costs (annual and quarterly) for both inpatient and outpatient sector; a binary indicator for positive costs; total number of outpatient physician visits, and detailed breakdowns of visits by general practitioners (GP) and specialists. Moreover, we study costs for prescription drugs and laboratory services. For all health care demand measures, we focus on illness-related costs and visits as accident-related health care demand is covered only for individuals not yet in the labor market.

2.3.2 Sample restrictions

Based on the institutional setting, with individuals transitioning to the adult health plan in the year after turning 18 years old, we focus our analysis on individuals born in December or January. We do so to ensure that the age difference is too small to directly affect health care demand. We further restrict our sample to individuals insured with CSS for a consecutive four years around the transition to adulthood, which reduces the sample by 20% to 17,715 individuals. This restriction is required because we need a three-years panel to perform our main estimation, pre-treatment balance tests and to study deductible choices in the adult health plan. Moreover, the considerable jump in the insurance premium when entering the adult health plan incentivizes individuals to switch health insurers.[11] To ensure that our treatment and control group are comparable, individuals must be additionally insured for a fourth year, representing the control's first year in the adult health plan. Although this restriction seems rather restrictive, we will show that using a relaxation of this restriction yields very similar results (see Table 2.A.2 in the Appendix).
In addition, we apply four minor sample restrictions (sample reductions in parentheses): First, we exclude females with pregnancies within the observational period because pregnant women

[10]This information can be used as a proxy for whether individuals or their parents pay health insurance costs. However, we cannot observe who ultimately pays the bills.
[11]In our sample, the probability to switch the health insurer is 2-times higher in this year. This observed jump in the leaving probability coincides with existing literature (see Figure 9.7 in Beck et al., 2013)

are exempted from cost-sharing in Switzerland (2.2%). Second, we remove individuals with extremely high costs in any of the considered years to prevent these outliers from distorting our results (4.8%). In particular, we exclude individuals with total annual costs of above CHF 13'000 or total annual outpatient costs of more than CHF 9,000.[12] Third, we exclude individuals from three cantons (Appenzell Inner Rhodes, Ticino, and Grisons) where school enrollment cutoffs align with the turn of the calendar year (5.3%). For these cantons, those born in December (treated) and those born in January (controls) are in a different school cohort, which may also affect health care demand.[13] Finally, we take steps to exclude individuals born on January 1st or December 31st. While birth scheduling is not a pervasive issue in Switzerland, as substantiated by Chuard and Chuard-Keller (2021), assigning January 1st as the hypothetical birth date, particularly for immigrants with unknown birth dates, is nevertheless a concerning practice. Thus, we opt to exclude this symmetric window surrounding the turn of the year (2.9%). All restrictions together result in a final sample of 15,159 individuals.

2.3.3 Descriptive statistics

Table 2.2 shows the descriptive statistics on the final sample, overall and separately for those born in December (7,275) and those born in January (7,884). The population studied is young and relatively healthy. On average, annual (illness-related) health care expenditures amount to approximately CHF 830 per patient at the onset of our observational period.[14] Moreover, hospitalizations among the young are rare with 2.5% of individuals having positive inpatient costs. In contrast to few hospitalizations, we observe for 81% of children at least some outpatient costs. Annual outpatient costs per individual average to CHF 757. Around 15% of these outpatient costs can be attributed to costs for prescription drugs and 10% to costs for laboratory services. On average, individuals have three physician visits per year, with approximately two GP visits and one specialist visit.

The majority of children are in the default child health plan with a zero deductible, resulting in an average deductible of only just over CHF 60. The health plan with free physician choice is slightly less common compared to managed-care health plans with gatekeeping. Moreover, 80% of the child health plans include accident coverage which indicates that four out of five 17-year-olds have not yet entered the labor market. In terms of individual characteristics, a bit less than half of our sample is female and the majority is Swiss and German-speaking. Finally, around 7.4% of children are classified as chronically ill. The most common chronic diseases in our sample of young adults are asthma (3.2%), attention deficit hyperactivity disorder (1.9%), and mental

[12] The two defined thresholds to identify the outliers represent approximately to the top 1% of the corresponding cost distributions.

[13] For instance, because those born in December likely enter the labor market earlier.

[14] This corresponds to around one fourth of the average annual health care expenditures of CHF 3,567 across all age cohorts (FOPH, 2022)

Table 2.2: Balance of covariates and pre-treatment outcomes

	Full sample	**Jan**	**Dec**	**Diff**	**P-val**
Annual pre-treatment health care use					
Total costs (CHF)	831	831	831	-0.037	0.999
Inpatient costs > 0	0.025	0.023	0.027	0.004	0.158
Inpatient costs (CHF)	73.3	67.1	79.9	12.8	0.148
Outpatient costs > 0	0.814	0.812	0.817	0.006	0.358
Outpatient costs (CHF)	757	764	751	-12.8	0.471
Drug costs (CHF)	117	118	116	-2.13	0.561
Laboratory costs (CHF)	80.5	79.8	81.3	1.55	0.592
No. of physician visits	3.05	3.06	3.04	-0.019	0.775
No. of GP visits	1.95	1.96	1.95	-0.011	0.807
No. of specialist visits	1.10	1.10	1.09	-0.008	0.849
Characteristics of child health plan					
Deductible	63.5	66.2	60.5	-5.62	0.030
No deductible	0.850	0.844	0.856	0.012	0.044
Free physician choice	0.452	0.451	0.452	0.001	0.869
Accident coverage	0.801	0.803	0.799	-0.005	0.474
Individual characteristics					
Female	0.468	0.460	0.477	0.017	0.040
Swiss Nationality	0.870	0.873	0.866	-0.006	0.252
German-speaking	0.702	0.706	0.697	-0.009	0.236
French-speaking	0.292	0.288	0.296	0.008	0.294
Italian-speaking	0.004	0.004	0.005	0.000	0.654
Chronically ill	0.074	0.076	0.072	-0.004	0.384
Observations	15,159	7,884	7,275		

Note: The table shows the mean pre-treatment outcomes in annual terms and mean characteristics for the full sample and separately for those born in December (treated) and those born in January (controls). Additionally, it records the difference-in-means between the two groups and the p-value of this difference. The pre-treatment period is defined as the year in which both groups are still in the child health plan in the current and the next year, referred to as $t = -1$ (see Section 2.4). The child health plan features and the individual characteristics are measured in $t = 0$, the last year in which both groups are in the child health plan.

and neurological diseases (0.8%) such as migraines, epilepsy or depression.[15] Individuals born in December and those born in January seem highly comparable in terms of their pre-treatment outcomes, their pre-treatment health plan choices and their individual characteristics. Only the proportion of females and the share of children in a zero-deductible plan differ statistically

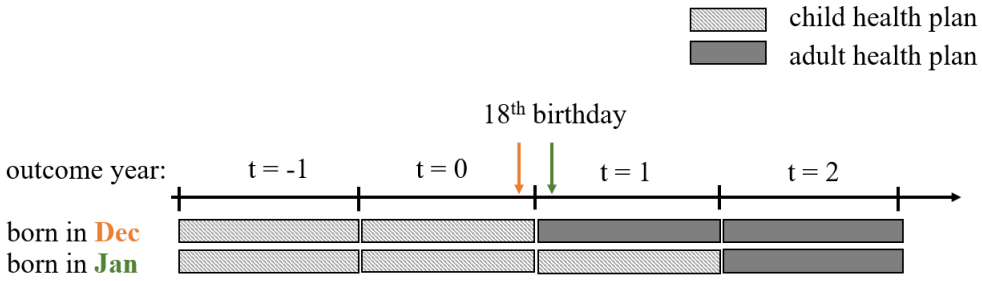
[15]We use data on pharmaceutical expenditure (pharmaceutical costs groups) to identify whether individuals suffer from a chronic disease.

significantly between the two groups. However, these differences are very small in size and economically not meaningful. Nevertheless, we analyze forward-looking behavior separately for females and males in the results section and estimate the effect for the subsample of children with zero deductible as a robustness check (see Table 2.A.2 in the Appendix).

2.4 Empirical strategy

We are interested in estimating the impact of next year's health care prices on current demand. However, this is challenging within systems incorporating deductibles. The deductible choice is endogenous. Individuals who expect high health care expenditures in the following year choose a lower deductible, whereas those anticipating lower expenditures opt for a higher deductible. This makes it challenging to causally identify the effect of an increase in cost-sharing on health care demand. We address this challenge by exploiting an exogenous variation in the deductible caused by entering the adult health plan in the year after turning 18 years old.

Figure 2.2: Exploiting the discontinuous transition to the adult health plan



Note: This figure illustrates our identification strategy. We exploit that individuals born in December, turning 18 slightly before the turn of the year, enter the adult health plan right after in January. In contrast, individuals turning 18 in January are in the child health plan for one more year. We refer to the last year where both groups are in the child health plan as $t = 0$, and the first year in the adult health plan of those born in December as $t = 1$. In $t = -1$, both groups are in the child health plan in the current and the following year. We can therefore use year $t = -1$ for balance checks and placebo tests.

Specifically, we compare individuals born in December, representing our treatment group ($D = 1$), with those born in January, representing our control group ($D = 0$). Treated individuals, who turn 18 in December, will enroll in an adult plan starting in January of the following year, which we denote with $t = 1$. In contrast, individuals in the control group, who turn 18 in January, will only join the same plan one year later (denoted with $t = 2$), despite being nearly the same age as those born in December. Our time indicator $t = 0$ consequently describes the period where both groups are still in the child plan but for those treated it is the last year, while the controls still enjoy another year of lower cost-sharing in the child plan. For balancing checks, we also look at the time period $t = -1$, where both groups face the same future price

in the next period. An overview of these respective time periods is given in Figure 2.2.
As deductibles range from CHF 0 to CHF 600 for children and CHF 300 to CHF 2500 for adults (see Table 2.1) and 85% of children are in the (standard) health plan with no deductible (see Table 2.2), an increase in the out-of-pocket price for health care is very likely when individuals enter the adult health plan. Table 2.3 confirms that, in our sample, 99.4% of those born in December ($D = 1$) experience a deductible increase in $t = 1$, while individuals hardly change their deductible as long as they remain in the child health plan. For instance, only 0.8% of the controls ($D = 0$) increase their deductible in $t = 1$. Similarly, treated and controls do not change their deductible in $t = 0$ when both are still in the child health plan.

Table 2.3: Deductible increase triggered by transition to adult plan

	D = 1	**D = 0**	**Diff**
Period t = 0			
Deductible decrease	0.004	0.005	-0.001
Deductible increase	0.009	0.008	0.001
Period t = 1			
Deductible decrease	0.005	0.003	0.001
Deductible increase	0.994	0.008	0.985

Note: The table depicts the share of individuals that increase (resp. decrease) their deductible in $t = 0$ and $t = 1$ in each case compared to the previous year.

Because the transition to the adult health plan is almost perfectly associated with an increase in the deductible and for sure results in a higher stop-loss amount, we apply Ordinary Least Squares (OLS) to estimate the effect of a future increase in cost-sharing on today's demand for health care.[16] Specifically, we estimate the following regression:

$$Y_{i,t=0} = \alpha + \beta D_i + \mu_y + \epsilon_i \tag{2.1}$$

To increase the precision of the estimation with multiple cohorts, we include year-fixed effects μ_y. The treatment dummy D_i is equal to one for individuals born in December. Therefore, β captures the reduced-form effect of the exogenous deductible (and stop-loss) increase in $t = 1$, induced by the transition from the child to the adult health plan, on various health care demand measures $Y_{i,t=0}$ in the current year $t = 0$.[17] Because we have almost perfect compliance with the treatment (see Table 2.3), this reduced-form OLS estimates hardly differ from the causal point estimates using an instrumental variable (IV) approach (see Section 2.A.1 in the Appendix).

[16]Consider that the stop-loss amount increases for all individuals from CHF 350 to 700. However, for the rather healthy population studied, the stop-loss amount is less important, while the deductible may matter a lot.
[17]Using count models for the number of annual visits and limited dependent variable models for health care costs produces very similar results, which is why we focus on OLS for simplicity.

For simplicity, we therefore refer to the estimated reduced-form effect, in what follows, as the causal effect of higher future out-of-pocket costs on current health care demand.[18]

To ensure the validity of β as an estimator of the causal effect, it is imperative to examine the exogeneity of the treatment. We argue that whether individuals are born in December or January is as-if randomly assigned. There are no confounders that determine both the individual's health care demand and whether an individual is born in December or January. As the birth month is determined at birth, the only possible way endogeneity could arise is, when parents strategically time the birth of their child. Given that tax benefits for parents in Switzerland depend on the age and educational status of their children, and considering that we restricted the sample to cantons in which treated and controls should be in the same school cohort, tax benefits are largely comparable across both groups. Chuard and Chuard-Keller (2021) further show that birth scheduling due to financial incentives, such as a birth allowance, is not a pervasive issue in Switzerland. Moreover, we demonstrate that our sample exhibits balance across nearly all predetermined characteristics and pre-treatment outcomes, as evidenced in Table 2.2. Although there are a few variables where statistically significant differences between those born in December and those born in January are observed, these differences hold minimal economic significance. Hence, we are confident that the exogeneity assumption holds in our setting.

We further assert that the only channel through which the birth month (December versus January) influences the health care costs is the fact that those born in December enter the adult health plan one year earlier while those born in January remain one year longer in the child health plan. By restricting the sample to those born in December or January, we can ensure that the slight age difference is too small to have a direct effect on the health care demand. In line with this argument, Table 2.2 shows that the slight age difference did not result in significant differences of health care demand pre-treatment. Furthermore, we undertake measures to ascertain that the cutoff from December to January does not coincide with other significant cutoffs within the Swiss context that could potentially influence the outcomes.[19,20] To mitigate this concern, we exclude three cantons for which school enrollment cutoffs align with the transition of the calendar year.

Now that we have ensured that the main assumptions likely hold, we present in the next section the results on forward-looking behavior, meaning the effect of the increase of the next year's health care prices on the current health care demand. Descriptive results on demand responses in the first year with higher cost-sharing ($t = 1$) are shown in Section 2.6.

[18]We perform additional robustness checks and discuss the application of further estimation methods such as regression discontinuity design (RDD) and Differences-in-differences (DiD) in Section 2.A.2 in the Appendix.

[19]Refer to Appendix 2.B for a discussion of why the obligation to serve in the military is unlikely to affect our results on forward-looking behavior.

[20]Moreover, note that, in Switzerland, disability insurance covers the treatments of congenital defects not only for children but young adults up to the age of 20 years.

2.5 Results on forward-looking behavior

Our main results presented in Table 2.4 suggest that anticipating the increase in next years' out-of-pocket price for health care leads to an increase in health care demand in the current year. Panel A indicates that the probability to have positive outpatient costs increases by 1.2 percentage points (or 1.5%). Moreover, the annual outpatient costs increase on average by CHF 39.7 (or 4.8%). Panel B reveals a significant increase in the probability to have a physician visit within the year preceding the out-of-pocket price increase. The probability increases by 1.7 percentage points for GPs (2.6%) and by 2.9 percentage points for specialists (7.2%), indicating that the effect on specialist visits is considerably more pronounced. Considering the overall number of physician visits per year, the estimates suggest that, on average, every sixth individual has an additional outpatient physician visit. Again the increase in the average number of outpatient visits is larger for specialists compared to GP visits. As expected, we find no significant impact of higher next year's out-of-pocket prices on today's demand for inpatient care. The need for inpatient care is less plannable and less elective. Therefore, individuals may find it harder to consume additional inpatient care or to shift inpatient care to periods with lower cost-sharing.

Table 2.4: Forward-looking behavior

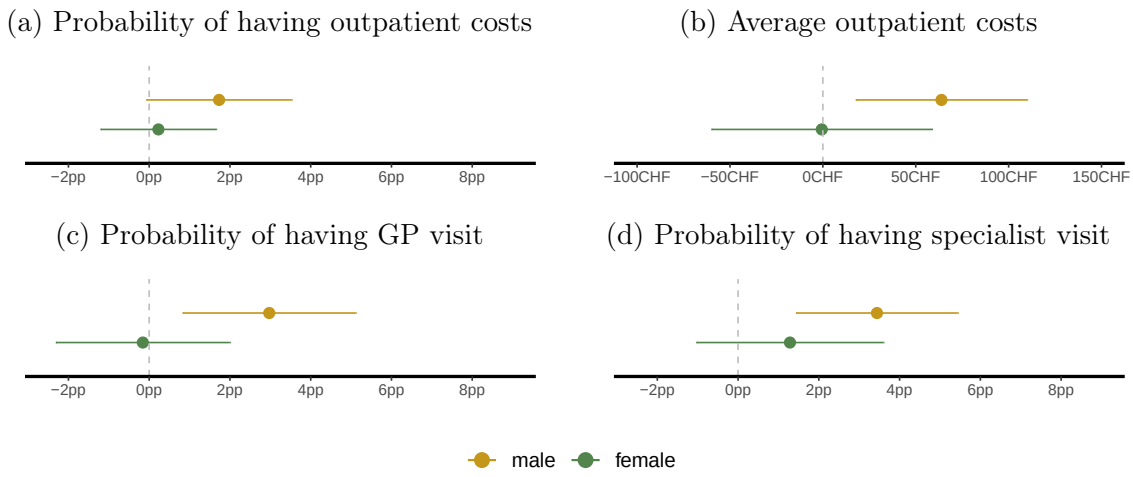
Dependent variable	Effect	P-value	Baseline
A. Annual outpatient costs			
Outpatient costs > 0	0.012	0.041	0.829
Outpatient costs (CHF)	39.7	0.038	823
B. Annual outpatient physician visits			
Physician visits > 0	0.022	0.001	0.738
GP visits > 0	0.017	0.031	0.633
Specialist visits > 0	0.029	0.000	0.402
Total number of physician visits	0.109	0.117	3.28
Number of GP visits	0.043	0.345	2.07
Number of specialist visits	0.066	0.145	1.21
C. Annual inpatient costs			
Inpatient costs > 0	0.001	0.820	0.027
Inpatient costs (CHF)	7.14	0.435	77.3

Note: This table presents the effect of an increase in next year's out-of-pocket prices (in year $t = 1$) on current health care demand (in year $t = 0$). The p-value is calculated based on heteroskedasticity-robust standard errors. The baseline represents the average outcome in the control group in the current year ($t = 0$). The estimation is performed on the final sample of 15,159 individuals with 7,275 treated individuals and 7,884 controls.

2.5.1 Heterogeneity in demand responses

A heterogeneity analysis reveals that the reported effects are mainly driven by male individuals. As depicted in Figure 2.3a, we estimate an increase of 1.7 percentage points (or 2.2%) in the probability of having positive outpatient costs for males, whereas for females the effect is considerably smaller and very close to zero. In terms of average outpatient costs (Figure 2.3b), our results show a significant increase in average per-patient costs of CHF 63.9 (or 9.8%) for males. In contrast, the point estimate is approximately zero for females. The same pattern also holds true for physician visits. Figure 2.3c shows that the probability of having a GP visit increases by 3 percentage points (or 5.1%) for males, whereas we observe essentially no change for females. The point estimate for females is -0.2 percentage points (-0.3%) and neither statistically nor economically different from zero. Our estimations in Figure 2.3d suggest a notable increase of 3.4 percentage points in young men's probability to visit a specialist, which corresponds to a relative increase of 12.1%. Our results might also indicate a slight increase in the probability of a specialist visits among females, although rather limited (1.3 percentage points; or 2.4%) and again not statistically different from zero. In Section 2.5.3, we are going to discuss potential explanations for this effect heterogeneity by sex.

Figure 2.3: Heterogeneity in forward-looking behavior by sex



Note: This figure shows the effects of higher next year's out-of-pocket prices (in $t = 1$) on current annual health care costs and physician visits (in $t = 0$) separately for male and female individuals. The point estimates represent the effects obtained from the OLS estimation in Equation (2.1). Heteroscedasticity-robust standard errors were used to calculate the 95% confidence intervals.

Interestingly, among men we also observe demand response heterogeneity related to health plan choices (see Table 2.C.2 in the Appendix). Compared to managed-care health plans with gatekeeping, the forward-looking behavior is much more pronounced among men in health plans with free physician choice. There are two potential explanations for this. First, it might suggest that gatekeeping in managed-care health plans works well, providing evidence that

individuals in these health plans have fewer possibilities to increase their health care demand due to restricted access.[21] In line with this argument, we observe a significant increase in GP visits of the same size for individuals in both health plan types, but no significant increase in average costs or specialists visits for individuals in the managed-care health plan. These findings indicate that, in managed-care plans, GPs might be able to prevent additional (potentially unnecessary) health care consumption. Second, individuals with a larger moral hazard tend to select into more generous health plans (Einav et al., 2013), which is in our setting the health plan with free physician choice. Due to the larger moral hazard, they may also react more strongly to future price changes and therefore, engage more heavily in forward-looking behavior.

Finally, we explore heterogeneity between language regions. Previous studies have shown that cultural and structural differences between Latin and German-speaking cantons lead to higher per-capita health expenditures in Latin cantons (see e.g., Crivelli et al., 2006). It is therefore interesting to study whether forward-looking behavior also varies across these two language regions. Our results in Table 2.C.3 suggest that male individuals in both regions exhibit forward-looking behavior.[22] Nevertheless, our results indicate that the effect on outpatient costs is higher in German-speaking cantons (CHF 80.2; or 13.3%) than in Latin cantons (CHF 30.8; or 4.01%).

2.5.2 Anticipatory spending by type of health care demand

As men seem to increase their demand today anticipating a future increase in out-of-pocket prices for health care, we now focus on male individuals only to study more closely for which health care services the demand expands.[23] The results in Figure 2.4a reveal that the probability of having positive drug costs or costs for laboratory services increases significantly, and more compared to the probability of having positive outpatient costs. Moreover, whereas the increase in the probability of positive outpatient costs in the second half of the year (i.e., Q3 and Q4) is sizable and highly significant, the propensity to have outpatient costs increases less strongly in the first two quarters of the year. Similarly, Figure 2.4b shows the increase in average costs by service type and by the quarter of service provision. To enhance the comparability across categories with different average annual (resp. quarterly) costs, Figure 2.4b depicts changes in average costs relative to their baseline.[24] On average, drug costs increase by approximately 8% and costs for laboratory services even by a little more than 10%. Figure 2.4b further shows that the average cost increase is strongest in the fourth quarter of the year. This aligns with

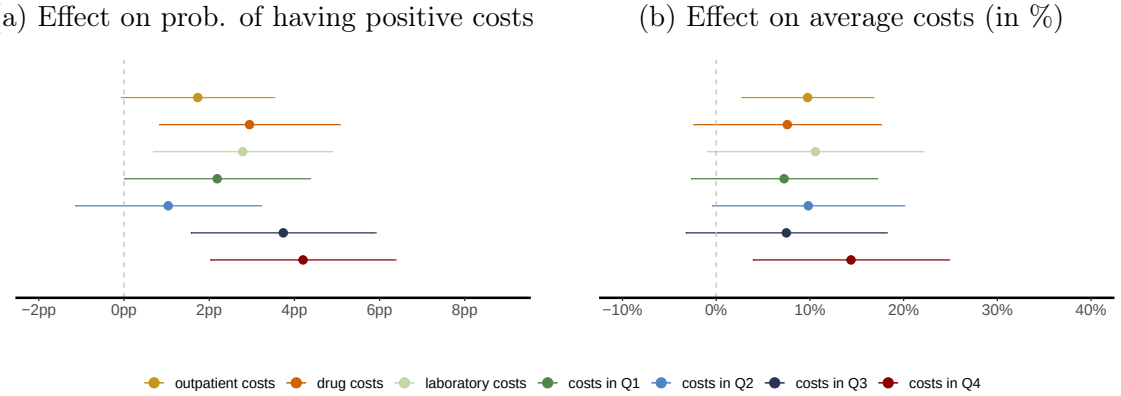
[21] There is ample evidence that managed-care in Switzerland successfully reduces health care costs (see e.g., Kauer, 2017; Trottmann et al., 2012), however, the reasons for the cost savings remain largely unknown.

[22] Note that, for Latin cantons, most effects are not statistically significant. However, we must consider the considerably smaller sample size for this subsample.

[23] For completeness, we also show the results for females in Table 2.C.1 in the Appendix.

[24] The average annual (resp. quarterly) costs in the control group (in $t = 0$) are used as the baseline.

Figure 2.4: Forward-looking behavior across different health care demand categories



Note: This figure shows the causal effect of higher next year's out-of-pocket prices (in $t = 1$) on various categories of annual health care costs and quarterly outpatient health care costs in the current year ($t = 0$) for male individuals (see Table 2.C.1 in the Appendix). Panel (a) depicts the effect (in percentage points) on the probability of having positive costs separately for different cost categories. Panel (b) shows the effect on average costs. We scale the effects in (b) by their corresponding average outcomes in $t = 0$ in the control group to improve comparability because different cost categories have different baselines. Heteroskedasticity-robust standard errors are used to calculate the 95% confidence intervals.

our expectations, considering that some health care needs cannot be advanced too far in time. Furthermore, some individuals may only become aware of the next year's cost-sharing increase after having received the new insurance policy in October.

2.5.3 Explanations for the effect heterogeneity

Our estimates suggest that men increase their health care use today in response to a future price increase. Hence, our results provide evidence for forward-looking behavior of male individuals. In contrast, we do not observe increased demand among females in anticipation of the price increase. The absence of such anticipatory spending, however, does not imply necessarily that female individuals are not forward-looking. It might be that males and females face different incentives due to inherent differences in their characteristics, in their pre-treatment health care consumption, and in their actual future price.

Table 2.5 reveals in fact significant differences in health care demand of females and males in the pre-treatment period. For example, average annual health care costs are significantly higher for females. Moreover, females are 8.5 percentage points (10.9%) more likely to have at least some health care cost pre-treatment compared to males. Our data suggests that females undergo regular check-ups as part of their gynecological screening. On average, almost every third female visits a gynecologist once a year with average costs of CHF 156 per visit.[25] As a result, females might have less room for additional health care demand in response to future

[25]These figures are calculated for period $t = 0$ using the control group (i.e., those born in January). These gynecologist visits might also partly explain the higher number of annual physician and specialist visits.

Table 2.5: Pre-treatment health care demand and health plan choices by sex

	Females	Males	Diff	P-value
Annual health care demand in $t = -1$				
Total costs (CHF)	953	720	233	0.000
Outpatient costs (CHF)	877	636	241	0.000
Costs > 0	0.862	0.777	0.085	0.000
Costs > 300	0.613	0.489	0.124	0.000
Costs > 2500	0.091	0.070	0.021	0.001
Number of physician visits	3.61	2.53	1.08	0.000
Number of specialist visits	1.43	0.786	0.645	0.000
Health plan in $t = 0$				
Free physician choice	0.442	0.462	-0.021	0.079
No deductible	0.854	0.857	-0.003	0.722
Deductible t=0	61.5	59.6	1.87	0.610
Accident coverage	0.172	0.228	-0.056	0.000
Health plan in $t = 1$				
Deductible CHF 300	0.588	0.554	0.034	0.003
Deductible CHF 500, 1000, 1500, or 2000	0.211	0.224	-0.013	0.175
Deductible CHF 2500	0.200	0.222	-0.022	0.024
Deductible t=1	976	1037	-61.3	0.004
Observations	3,469	3,806		

Note: This table shows sex-specific average pre-treatment outcomes and health plan choices for treated individuals (i.e., born in December). The p-value indicates whether pre-treatment outcomes and/or health plan choices differ statistically significantly between female and male individuals in the treatment group. P-values are calculated using heteroskedasticity-robust standard errors.

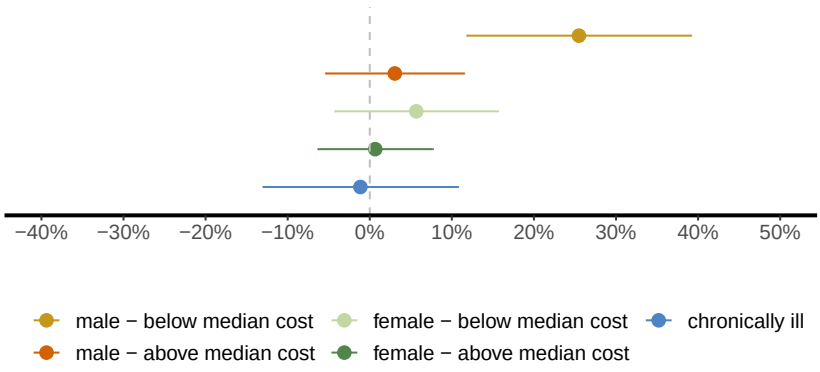
price increases. In contrast, male individuals might take the opportunity to do a final check-up in the period where cost-sharing is still low. They may also do so to better assess their health state to decide which deductible to choose for $t = 1$. This argument is supported by the observed increase in laboratory costs among male individuals.

Moreover, as depicted in Table 2.5, females are 12.4 percentage points (25.4%) more likely to have pre-treatment costs in $t = -1$ exceeding CHF 300. Disregarding potential moral hazard for the moment, they might also exceed this amount in $t = 1$, which corresponds to the lowest selectable deductible of CHF 300 in $t = 1$. In fact, almost 60% of females choose this lowest deductible for $t = 1$, their first year in the adult health plan. While the deductible choices in the child health plan do not significantly differ between females and males, females are 3.4 percentage points (or 6.1%) more likely to choose the lowest deductible and males more

often (2.2 percentage points; or 9.9%) choose the highest deductible of CHF 2,500 in $t = 1$. As a result, male individuals, on average, face a higher increase in out-of-pocket cost when entering the adult health plan. Moreover, ex-post around 47% of females reach the deductible compared to only 34% of males. Although deductible choices and health care costs are (partly) endogenous, females and males could fundamentally differ in their (expected) future price, which in turn would imply that females have fewer incentives to increase their demand in $t = 0$. Furthermore, male individuals are slightly more likely to be in a free-physician-choice health plan in $t = 0$ which we have shown is the plan type in which forward-looking behavior seems to be more pronounced. Finally, males are more often employed at the age of 17 years, indicated by their lower share of children with accident coverage in $t = 0$, which might also explain differences in health care consumption behavior and price sensitivity.

To test our conjecture that the larger health care utilization is one reason for the absence of any significant effect for females, we estimate our specification separately for female and male individuals with pre-treatment costs above and below their respective median and for chronically ill individuals. Our findings in Figure 2.5 suggest that, anticipating the cost-sharing increase in the next year, low-cost females might also slightly increase their health care demand (albeit not statistically significantly). The point estimate (in relative terms) is higher for low-cost females (5.7%) compared to high-cost males (3.1%). Moreover, the effect among male individuals is mainly driven by low-cost / "healthier" individuals. For individuals classified as chronically ill, we find no reaction in health care demand.[26]

Figure 2.5: Heterogeneity in forward-looking behavior by low-cost and high-cost individuals



Note: This figure shows the causal effect of higher out-of-pocket prices in $t = 1$ on outpatient costs in $t = 0$, separately for males and females with costs above and below their sex-specific pre-treatment median costs, and for chronically ill individuals. The point estimates represent the OLS estimates based on Equation (2.1) for the respective subsample. Because baseline costs differ between the five groups, effects relative to the corresponding baseline costs are depicted to improve comparability. Heteroskedasticity-robust standard errors are used to calculate the 95% confidence intervals. For detailed estimation results, we refer to Table 2.C.4 in the Appendix.

[26]Note that these findings do not contradict the evidence on anticipatory spending of elderly, chronically ill individuals documented in previous studies (see e.g., Alpert, 2016; Einav et al., 2015; Johansson et al., 2023), as compared to these studies, our high-cost children are still relatively healthy / low-cost.

2.6 Demand shifting or extra demand

As shown in the previous section, we find evidence for forward-looking behavior among the young, mainly among healthy young men. There are, however, two mechanisms that could explain the observed anticipatory spending before the deductible increase. On the one hand, forward-looking individuals could shift demand from $t = 1$ to $t = 0$. In this case, there is no overall increase in demand and individuals just reallocate their demand in order to reduce their financial burden. On the other hand, the forward-looking behavior could lead to an actual increased demand, that is, the health care spending would not have occurred (in a later period) if there was no deductible increase. For instance, forward-looking individuals could visit a physician to check their health status before entering the adult health plan and choosing the adult deductible. In order to investigate whether the forward-looking behavior is demand shifting or extra demand, we have to consider health care consumption in $t = 1$.

When comparing the treatment and the control group in $t = 1$, there are four potential causes for differences in the health care costs. First, and our main interest, demand shifting of the treatment group. If the treatment group shifts demand from $t = 1$ to $t = 0$, their average demand will be smaller in $t = 1$ than the demand of the control group. Second, classic moral hazard of the treatment group. In $t = 1$, most treated individuals have a higher deductible and therefore face a higher out-of-pocket price for health care. As a result, their demand could be lower than without the price increase. Third, forward-looking behavior of the *control* group. Recall that individuals in the control group are in the last year in the child health plan in $t = 1$, that is, after this year they will face also the transition into the adult health plan. Consequently, the control group could exhibit higher costs in $t = 1$ due to forward-looking behavior. Note that these three causes increase the spread in the health care costs of the treatment and the control group. Fourth, the considerable jump in the insurance premium when entering the adult health plan likely triggers individuals to revisit their health plan choices and to switch to managed-care health plans to get a premium discount. Our data suggests that the share of individuals with a free-physician-choice health plan reduces by 14.8 percentage points (or 32.7%) when transitioning to the adult health plan, whereas in our control group only 2.9% switch to a managed-care health plan in $t = 1$ (see Table 2.C.5). This might represent a further channel for differences in health care costs between treatment and control group in $t = 1$.[27]

In what follows, we have to consider an additional source of cost "differences". The treatment group could have fewer incentives to submit their health care bills to the insurer as they are less likely to exceed the deductible. There are two systems how insurers receive the health care bills of their customers. In the so-called "payer" system, the health care provider sends the bill directly to the insurer of the patient; in the "guarantee" system, the health care provider

[27] For male individuals, the obligation to serve in the military might be an additional channel affecting health care demand in $t = 1$ (see Appendix Section 2.B).

sends the bill to the patient, which has to forward it to the insurer to get reimbursed. Which system applies depends on various factors, see Schmid (2017) for more details. Importantly, individuals do not have an incentive to submit their bills under the guarantee system if they do not exceed their deductible. As a result, the *observed* health care expenditures of the treatment group could be smaller than their actual expenditures and therefore increase the difference in (observed) health care costs between the treatment and the control group. Consequently, in what follows, we are going to compare only costs from bills processed in the payer system which covers around two thirds of total health expenditures.[28]

Table 2.6 reports descriptive differences in average outpatient costs in $t = 1$ between treatment and control group. Panel A reveals that average outpatient costs from bills processed in the payer system do not significantly differ between males in the treatment and the control group. It is, therefore, very unlikely that male individuals shift their demand from $t = 1$ to $t = 0$. In other words, the demand increase in the year before entering the adult health plan seems to be additional. Given that we find no evidence for anticipatory spending among females, a decrease in health care demand among treated females could indicate that females engage in moral hazard behavior, consuming less in period $t = 1$ when they face higher out-of-pocket costs. Panel B shows a slight decrease in the probability to have outpatient costs of 1.8 percentage points (or 2.3%). However, there is no significant difference in average payer-system processed outpatient costs between treated females and controls. Hence, if any, moral hazard behavior seems limited among young females.

Table 2.6: Descriptive differences in health care demand in $t = 1$

Dependent Variable	$D = 0$	$D = 1$	Diff	P-value
A. Male individuals				
Outpatient costs (payer system)	428	437	8.63	0.639
Outpatient costs > 0 (payer system)	0.631	0.625	-0.006	0.575
Observations	4,182	3,663		
B. Female individuals				
Outpatient costs (payer system)	669	651	-17.8	0.446
Outpatient costs > 0 (payer system)	0.784	0.766	-0.018	0.077
Observations	3,627	3,466		

Note: For this analysis, we excluded 221 individuals (or 1.5%) that suspended their health insurance during (part of) year $t = 1$, probably starting to serve the military.

[28] Although the incentives incorporated in the guarantee system should not affect choices of individuals in the child health plan (majority in plan with no deductible), we report in Appendix Table 2.C.1 Panel D estimates of forward-looking behavior on bills from the payer system only. The results are comparable to our main results.

2.7 Conclusion

Most health care systems apply cost-sharing to increase efficiency. As cost-sharing is mostly based on annual health care expenditures, individuals often exhibit a sharp change in the out-of-pocket price at the turn of the year. Such discontinuous changes in out-of-pocket prices for health care over time create considerable, dynamic incentives. If individuals consider future out-of-pocket prices and optimize their health care consumption across years, they are expected to react to these dynamic incentives. As a consequence, such forward-looking behavior weakens the effectiveness of cost-sharing.

Indeed, our results suggest that young men increase their health care demand in the year preceding the exogenous increase in cost-sharing. Hence, we find evidence that young men are forward-looking, consuming more health care today if they expect an increase in out-of-pocket costs tomorrow. In contrast, young women seem not to adjust their health care consumption. However, they may also have lower incentives to do so for two reasons. First, out-of-pocket costs increase less because females more often choose the lowest deductible of CHF 300 in the adult health plan. Second, based on their past health care demand, females are more likely to reach their deductible in the next year lowering their expected benefits from anticipatory spendings. So far, studies mainly analyzed forward-looking behavior among specific, rather sick population subgroups (see e.g., Alpert, 2016; Einav et al., 2015; Johansson et al., 2023). Our study contributes to this literature showing that even healthy individuals react to dynamic incentives. Instead of re-timing, however, they seem to simply consume more health care in the period before the cost-sharing increase. These findings have important implications for optimal health plan design. Because individuals seem to respond to dynamic incentives, cost-sharing based on annual health care expenditures, resulting in a discontinuous change of cost-sharing at the turn of the year, might not be the optimal approach.

Although we observe demand responses to changes in out-of-pocket prices, it is important to note that we cannot conclude on whether lower cost-sharing leads to overuse of health care as we have no information on the optimal health care consumption. Nevertheless, studying whether individuals under-consume health care in periods with high cost-sharing or over-consume in periods with low cost-sharing would be an interesting question for future research. Moreover, we cannot identify whether the observed changes in health care demand is driven by the children itself or their parents.[29] Finally, due to the various factors that may influence health care demand during the treatment group's first year in the adult health plan, for this period, our setting allows only exploratory analyses and discussions of potential underlying mechanisms. We therefore encourage further research in this regard.

[29]Note that for the vast majority of individuals aged below 20 years, the parents are recorded as invoice recipients.

2.A Robustness checks

2.A.1 Instrumental variable approach

Technically, not all individuals necessarily experience an increase in their deductible when transitioning from the child to the adult health plan. Because children deductibles range from CHF 0 to CHF 600 and adult deductibles from CHF 300 to CHF 2500 (see Table 2.1), it is possible that treated individuals reduce their deductible when entering the adult health plan or controls increase their deductible while still remaining in the child health plan. Our OLS estimation in the main part of the paper, therefore, identifies a reduced-form effect. However, as shown in Table 2.3, the two cases mentioned are very rare. Almost all treated individuals face an increase in their deductible when entering the adult health plan, whereas most controls, staying in the child health plan for one more year, experience no change in their deductible with the start of the next year. Nevertheless, for completeness, we provide the results of an instrumental variable (IV) approach to identify the causal effect of the next year's increase in out-of-pocket prices on current health care demand for the subgroup of compliers.

To estimate the local average treatment effect (LATE), we use two stage least squares (2SLS). First, we estimate the following first stage regression including year fixed effects, μ_y, to increase precision:

$$D_{i,t1} = \alpha + \beta Z_i + \mu_y + \epsilon_i \ , \tag{2.A.1}$$

where Z_i is an binary variable equal to one for individuals born in December and $D_{i,t1}$ is a binary variable equal to one for individuals that experience an increase in their deductible in $t = 1$.

Second, we use the predicted probability of a deductible increase in $t = 1$, $\widehat{D_{i,t1}}$, to estimate the causal effect of anticipating future out-of-pocket price increases on health demand measures in the current year:

$$Y_{i,t=0} = \gamma + \delta \widehat{D_{i,t1}} + \eta_y + \nu_i \ , \tag{2.A.2}$$

To obtain consistent estimates of the effect, we need to impose three assumptions: exogeneity, exclusion and relevance of the instrument. We already argued in the main part of this paper that whether individuals are born in December or January should be as-if randomly assigned. Additionally, we showed that covariates are largely balanced. Moreover, we find no evidence that the slight age difference affects health care demand in the pre-treatment year, which supports the exclusion restriction. In addition, measures were taken to ensure that the cutoff does not align with other relevant cutoffs within the Swiss context. Finally, we have a strong first stage (see Table 2.A.1 Panel B) with almost all individuals born in December experiencing

a deductible increase in $t = 1$, whereas those born in January do not change their deductible in $t = 1$.

Due to almost perfect compliance, we expect the results from the IV estimation to be very similar to the results from the OLS estimation. The estimated local average treatment effects on average outpatient costs in Table 2.A.1 confirm that IV and OLS results are essentially the same. To avoid unnecessarily complicating the analysis, we focus on the OLS results in the main part of this paper.

Table 2.A.1: IV approach

Dependent variable	Estimate	P-value	Baseline	N obs
A. Local average treatment effect				
Outpatient costs $t = 0$	40.3	0.038	823	15,159
Outpatient costs $t = 0$ (males)	64.8	0.007	655	8,062
Outpatient costs $t = 0$ (females)	-0.604	0.984	1020	7,097
B. First stage				
Deductible increase $t = 1$	0.985	0.000	0.008	15,159
Deductible increase $t = 1$ (males)	0.985	0.000	0.011	8,062
Deductible increase $t = 1$ (females)	0.986	0.000	0.005	7,097

Note: The point estimates in Panel A show the local average treatment effect of a future increase in out-of-pocket price of health care on current health care demand using two stage least squares. The reported standard errors are heteroskedasticity-robust. Year-fixed are used to increase the precision of the estimation with multiple cohorts. The point estimates from the first stage in Panel B reveal the difference in the probability of having a deductible increase in $t = 1$ between those born in January ($Z = 0$) and those born in December ($Z = 1$).

2.A.2 Additional robustness checks

To asses the validity of our empirical strategy, we perform several further robustness checks, reported in Table 2.A.2. First, we estimate our OLS specification using pre-treatment outpatient costs from year $t = -1$ as the outcome. In this year, we expect no significant difference in costs between those born in December and those born in January, as both groups are still in the child health plan in the next year and therefore, both groups benefit from low out-of-pocket prices for another year. Our results in Panel A confirm that there is no significant difference in outpatient costs in $t = -1$ between treatment and control group, for both male and female individuals.[30]

[30]Table 2.2 has already shown that average pre-treatment outpatient costs do not significantly differ between treatment and control group for the full sample. Here, we show it separately for male and female individuals and use Equation (2.1), adapted for year $t = -1$, which additionally includes year fixed effects.

Table 2.A.2: Additional robustness checks

Dependent variable	Subsample	Window	Weights	Estimate	P-value	Baseline	N obs
A. Placebo test							
Outpatient costs $t = -1$	-	+/- 30 days	Uniform	-11.7	0.509	757	15,159
Outpatient costs $t = -1$	Males	+/- 30 days	Uniform	-5.5	0.802	639	8,062
Outpatient costs $t = -1$	Females	+/- 30 days	Uniform	-28.4	0.313	892	7,097
B. Sample restrictions							
B.1. Varying window around cutoff							
Outpatient costs $t = 0$	-	+/- 20 days	Uniform	35.2	0.128	821	5,293
Outpatient costs $t = 0$	Males	+/- 20 days	Uniform	60.0	0.032	647	2,881
Outpatient costs $t = 0$	Females	+/- 20 days	Uniform	-11.2	0.763	1027	2,412
Outpatient costs $t = 0$	-	+/- 10 days	Uniform	19.7	0.553	849	2,648
Outpatient costs $t = 0$	Males	+/- 10 days	Uniform	73.2	0.069	663	1,441
Outpatient costs $t = 0$	Females	+/- 10 days	Uniform	-54.9	0.309	1071	1,207
B.2. Children with zero deductible							
Outpatient costs $t = 0$	-	+/- 30 days	Uniform	40.7	0.054	880	12,879
Outpatient costs $t = 0$	Males	+/- 30 days	Uniform	62.9	0.016	720	6,851
Outpatient costs $t = 0$	Females	+/- 30 days	Uniform	4.60	0.890	1062	6,028
B.3. Sample with relaxed restr.							
Outpatient costs $t = 0$	-	+/- 30 days	Uniform	28.8	0.104	848	17,731
Outpatient costs $t = 0$	Males	+/- 30 days	Uniform	52.1	0.017	688	9,413
Outpatient costs $t = 0$	Females	+/- 30 days	Uniform	-6.02	0.830	1028	8,318
C. Weighting							
Outpatient costs $t = 0$	-	+/- 30 days	Triangular	23.3	0.291	830	15,159
Outpatient costs $t = 0$	Males	+/- 30 days	Triangular	55.5	0.037	655	8,062
Outpatient costs $t = 0$	Females	+/- 30 days	Triangular	-27.3	0.441	1038	7,097
Outpatient costs $t = 0$	-	+/- 30 days	Epanech.	28.5	0.173	827	15,159
Outpatient costs $t = 0$	Males	+/- 30 days	Epanech.	57.8	0.023	653	8,062
Outpatient costs $t = 0$	Females	+/- 30 days	Epanech.	-19.5	0.561	1033	7,097
D. Difference-in-difference							
Outpatient costs $t = 0$	-	+/- 30 days	Uniform	51.1	0.050	823	30,318
Outpatient costs $t = 0$	Males	+/- 30 days	Uniform	69.0	0.032	655	16,124
Outpatient costs $t = 0$	Females	+/- 30 days	Uniform	28.1	0.497	1020	14,194

Note: This table presents results on forward-looking behavior applying different estimation methods and sample restrictions. P-values are calculated based on heteroskedasticity-robust standard errors.

Second, we test whether our results are robust to slight modifications of the sample. In Panel B.1, we show results based on smaller windows around the cutoff, to trade off the plausibility of exclusion and exogeneity against the sample size. Specifically, we estimate our specification for female and male individuals with a birthday within 20 and 10 days of the turn of the year instead of 30 days. The patterns for the different windows are fairly similar, there is a positive significant effect for male individuals, whereas female individuals do not significantly change their health care demand in the year preceding the increase in the out-of-pocket price. In Panel

B.2, we estimate the effect for the subsample of children in a zero-deductible child health plan. This ensures that all treated individuals necessarily face an increase in their deductible when entering the adult health plan. Moreover, it controls for the slight difference in the proportions of zero-deductible plans between the treatment and the control group as depicted in Table 2.2. Again, the estimates are very close to our main results in the paper. Moreover, in Panel B.3, we relax the sample restrictions allowing individuals to switch their insurer in $t = 1$. Panel B.1 suggests that relaxing this sample restriction results in similar albeit somewhat smaller point estimates.

We additionally considered using the regression discontinuity design (RDD). Recall that we compare average health care demand between those born shortly before and those born shortly after the turn of the year. Hence, we have a setting with a discrete running variable (birth date) and few mass points (30 days before and 30 days after the turn of the year). According to Cattaneo et al. (2023), due to the low number of mass points close to the cutoff, the commonly used continuity-based approach to RD analysis does not appeal to our setting. It is recommended to use the local randomization approach to RD analysis instead (see Cattaneo et al., 2023, for details). The local randomization approach assumes that the treatment is as-if randomly assigned near the cutoff (i.e., the turn of the year) and can therefore be interpreted as a randomized experiment near the turn of the year. However, this implies that the outcomes are independent of the running variable (birth date). In contrast to the continuity-based approach, there is hence no direct effect of age on the outcome in the narrow window around the turn of the year. Under these assumptions, however, the local randomization approach is essentially a simple difference-in-means estimation as performed with OLS. Considering that the comparability of observations is even more plausible near the cutoff, RDD usually applies higher weights to these observations. We, therefore, also provide the results of weighted OLS estimation using triangular and epanechnikov kernels in Panel C. Again, the results are hardly sensitive to the application of different weights.

Finally, the estimates in Panel D of Table 2.A.2 result from a difference-in-difference (DiD) approach using whether individuals enter the adult health plan in the following year (i.e., born in December) as exogenous treatment indicator. DiD controls for potential pre-treatment differences in the level of health care costs between those born in December and those born in January. While it allows for such level differences in costs, it requires the two groups to follow the same cost trend (for details on the method see e.g., Cunningham, 2021). The magnitude of the point estimates overall and for males are highly comparable, whereas the estimate for females is somewhat higher but still not significant and, especially in relative terms, much smaller than for males. In summary, our results are fairly robust to using alternative estimation methods and applying different sample restrictions.

2.B Military service and health care demand

Within the Swiss context, there is, to our knowledge, only one cutoff that coincides with the cutoff from December to January in the year where those born in December turn 18.[31] Male individuals are invited to the military orientation day in the year in which they turn 18. However, we are confident that this does not explain our estimated effects for male individuals for several reasons. First, the orientation days take place throughout the year, but our effect is most pronounced in the fourth quarter of the year. Second, at the orientation day, young men are solely informed about the military service and their options. There is no medical checkup performed. The test for military fitness is an integral part of the recruitment day which no longer depends on birth year but rather school cohort and takes place around three to twelve months before joining the military service, and the earliest at the age of 18 years. Moreover, in our sample, no one serves in the military in the year they turn 18 ($t = 0$) and only few (3%) serve in the military in the year they turn 19 years ($t = 1$).[32] Therefore, it is very unlikely that potential health care demand related to serving in the military or to the recruitment day affects our analysis of forward-looking behavior. Third, we performed a heterogeneity analyses to assess whether our estimated "forward-looking behavior" is more pronounced among cantons with lower rates of military fitness. If this is the case, this could indicate that our estimated effect is partly driven by young men visiting physicians to obtain medical certificates to avoid military services. However, Table 2.B.1 suggests that the effect is considerably higher among cantons with higher rates of military fitness and not statistically significant for cantons with low rates of military fitness.

Table 2.B.1: Heterogeneity in forward-looking behavior by low/high military fitness cantons

Dependent varialbe	Military fitness	Effect	P-val	Baseline	N obs
Outpatient costs > 0	high	0.033	0.023	0.767	3,421
Outpatient costs > 0	low	0.005	0.659	0.794	4,641
Outpatient costs	high	96.0	0.004	626	3,421
Outpatient costs	low	43.3	0.181	727	4,641

Note: The table depicts the effect of higher future out-of-pocket prices on current health care demand separately for cantons with below median (low) and above median (high) military fitness rates. Data on canton-level military fitness rates was retrieved from press releases on *https://www.vtg.admin.ch/*

[31] Recall that we controlled for school cutoffs that aligned with the turn of the year in our sample restrictions.
[32] We use the share of individuals that suspend their health insurance contract as a proxy for serving the military. During military service, individuals are covered by military insurance and are allowed to suspend mandatory health insurance. Apart from military service, there are further reasons for suspending health insurance contracts (e.g., emigration). Hence, our measure represents an upper bound.

Nevertheless, military service might affect health care demand in $t = 1$ (discussed in Section 2.6), the year in which those treated turn 19, as young men usually visit the recruitment day with 19 years and start serving in the military with 19 or 20 years.[33] Their health care demand might increase or decrease due to their obligation to serve in the military. For instance, they might visit their GP or a psychiatrist with the aim to be exempted from military service for medical reasons. Conversely, they might postpone medical treatments to benefit from the absence of cost-sharing in the military insurance. However, if we have managed to ensure that the treatment and control groups are in the same school cohort, this effect should be evenly distributed between the two groups.

[33]This corresponds to the year $t = 2$ in our setting. Data confirms that around 15% suspend health insurance in year $t = 2$, indicating that they serve the military during the year $t = 2$.

2.C Additional tables

Table 2.C.1: Heterogeneity in forward-looking behavior by sex

	Males			Females		
Dependent variable	Effect	P-value	Baseline	Effect	P-value	Baseline
A. Annual health care use						
Physician visits > 0	0.033	0.001	0.665	0.005	0.607	0.824
GP visits > 0	0.030	0.007	0.584	-0.002	0.887	0.690
Specialist visits > 0	0.034	0.001	0.280	0.013	0.277	0.545
Number of physician visits	0.208	0.012	2.56	-0.057	0.615	4.14
Number of GP visits	0.154	0.008	1.74	-0.105	0.138	2.46
Number of specialist visits	0.054	0.287	0.821	0.049	0.528	1.67
B. Annual health care costs						
Outpatient costs > 0	0.017	0.059	0.775	0.002	0.754	0.893
Inpatient costs > 0	0.002	0.523	0.023	-0.002	0.709	0.032
Laboratory costs > 0	0.028	0.010	0.352	0.003	0.794	0.591
Drug costs > 0	0.029	0.006	0.606	-0.010	0.347	0.732
Outpatient costs	63.9	0.007	655	-0.596	0.984	1020
Inpatient costs	14.8	0.221	66.0	-2.70	0.846	90.4
Drug costs	7.97	0.138	105	-5.76	0.306	140
Laboratory costs	6.77	0.073	63.9	3.41	0.561	136
C. Quarterly health care costs						
Outpatient costs Q1 > 0	0.022	0.049	0.456	0.010	0.392	0.604
Outpatient costs Q2 > 0	0.010	0.351	0.454	0.000	0.982	0.600
Outpatient costs Q3 > 0	0.037	0.001	0.418	0.005	0.645	0.573
Outpatient costs Q4 > 0	0.042	0.000	0.425	0.006	0.605	0.601
Outpatient costs Q1	12.6	0.153	174	-4.594	0.668	261
Outpatient costs Q2	16.1	0.061	164	0.466	0.965	258
Outpatient costs Q3	11.3	0.172	151	3.488	0.731	228
Outpatient costs Q4	23.8	0.007	165	0.044	0.997	274
D. Costs processed with "payer" system only						
Outpatient costs (payer system) > 0	0.032	0.003	0.606	0.003	0.738	0.760
Outpatient costs (payer system)	49.3	0.008	413	12.5	0.583	626
Observations			8,062			7,097

Note: This table presents the sex-specific effects of increased future out-of-pocket prices ($t = 1$) for health care on today's demand for health care ($t = 0$) estimated using OLS based on Equation (2.1). P-values are calculated based on heteroskedasticity-robust standard errors.

Table 2.C.2: Heterogeneity in forward-looking behavior by health plan type

	Free physician choice			Managed-care plans		
Dependent variable	Effect	P-value	Baseline	Effect	P-value	Baseline
A. Annual health care use						
Physician visits > 0	0.052	0.000	0.689	0.016	0.257	0.644
GP visits > 0	0.041	0.010	0.599	0.019	0.195	0.572
Specialist visits > 0	0.057	0.000	0.311	0.014	0.283	0.254
Number of physician visits	0.273	0.025	2.74	0.154	0.168	2.41
Number of GP visits	0.139	0.100	1.81	0.167	0.034	1.68
Number of specialist visits	0.134	0.081	0.926	-0.013	0.846	0.733
B. Annual health care costs						
Outpatient costs > 0	0.037	0.004	0.791	0.000	0.973	0.761
Laboratory costs > 0	0.033	0.043	0.374	0.024	0.093	0.333
Drug costs > 0	0.038	0.016	0.636	0.022	0.132	0.581
Outpatient costs	95.7	0.008	711	36.1	0.243	608
Drug costs	17.8	0.066	122	-0.930	0.867	90.8
Laboratory costs	6.96	0.255	70.7	6.23	0.185	58.2
Observations			6,847			8,312

Note: This table presents the males' health plan type-specific effects of increased future out-of-pocket prices for health care (in $t = 1$) on today's demand for health care (in $t = 0$) estimated using OLS based on Equation (2.1). P-values are calculated based on heteroskedasticity-robust standard errors.

Table 2.C.3: Heterogeneity in forward-looking behavior by language region

	German-speaking cantons			Latin cantons		
Dependent variable	Effect	P-value	Baseline	Effect	P-value	Baseline
A. Annual health care use						
Physician visits > 0	0.033	0.008	0.660	0.033	0.083	0.675
GP visits > 0	0.028	0.034	0.590	0.033	0.105	0.568
Specialist visits > 0	0.031	0.009	0.256	0.046	0.019	0.335
Number of physician visits	0.195	0.045	2.55	0.239	0.126	2.58
Number of GP visits	0.135	0.056	1.81	0.201	0.043	1.57
Number of specialist visits	0.060	0.286	0.740	0.038	0.719	1.01
B. Annual health care costs						
Outpatient costs > 0	0.019	0.099	0.759	0.016	0.324	0.810
Laboratory costs > 0	0.030	0.023	0.376	0.025	0.190	0.291
Drug costs > 0	0.024	0.059	0.600	0.043	0.030	0.618
Outpatient costs	80.2	0.003	605	30.8	0.515	769
Drug costs	6.42	0.255	97.9	11.4	0.355	121
Laboratory costs	6.33	0.141	65.0	7.30	0.343	60.7
Observations			10,636			4,488

Note: This table presents the males' effects of increased future out-of-pocket prices for health care (in $t = 1$) on today's demand for health care (in $t = 0$) estimated using OLS based on Equation (2.1), separately by language region. Latin cantons include French- and Italian-speaking cantons. P-values are calculated based on heteroskedasticity-robust standard errors.

Table 2.C.4: Heterogeneity in forward-looking behavior by sex and pre-treatment costs

Sample	Effect	Effect (in %)	P-value	Baseline	N obs
Dependent variable: Annual outpatient costs (in CHF)					
high-cost females	8.89	0.668	0.852	1,332	3,333
low-cost females	30.2	5.67	0.264	533	3,333
high-cost males	26.7	3.05	0.479	874	3,725
low-cost males	80.6	25.5	0.000	316	3,725
chronically ill individuals	-20.5	-1.14	0.851	1,795	1,043

Note: This table presents the effects of higher next year's out-of-pocket prices (in $t = 1$) on current outpatient cost (in $t = 0$), separately by sex and by group of individuals with high (above median) and low (below median) pre-treatment health care costs (measured in $t = -1$). The effects are estimated using OLS based on Equation (2.1). P-values are calculated based on heteroskedasticity-robust standard errors.

Table 2.C.5: Reconsideration of health plan choice

	Share in managed-care plan			
D	$t = 0$	$t = 1$	Diff (pp)	Diff (%)
1	54.8%	69.6%	14.8	27.0
0	54.9%	56.5%	1.6	2.9

Note: This table depicts the proportions of individuals in managed-care health plans − in contrast to a free-physician-choice plan − in a given year ($t = 0$ or $t = 1$) separately for treated ($D = 1$) and controls ($D = 0$).

Chapter 3

Perils of one-size-fits-all policies: Evidence from tobacco markets

joint with Anna Nicolet, Catherine Maclean, Joachim Marti, and Michael Pesko

Abstract

In this study, we demonstrate the importance of considering heterogeneity in individuals' preferences over health-related products for public health policy design. While to date most public health policies do not account for heterogeneity across consumers, we study the potential value of tailoring public health policy based on such information. We focus on a complex, heavily regulated market − tobacco products − in which consumers use products for substantially different purposes, some of which may harm health and others which may reduce adverse health effects of smoking. Consequently, consumers have different preferences over products and their features. This setting suggests that 'one-size-fits-all' policies may not lead to the desired outcome, which is to reduce overall tobacco consumption and to encourage smokers to consume less harmful products. We conduct a discrete choice experiment with 3,500 U.S. adult smokers to predict responses of different smoker types to tobacco policies targeting nicotine, flavors, prescription, and prices (hassle and financial). Our results suggest that accounting for preference heterogeneity facilitates better prediction of various, often contradicting policy reactions and therefore enables more informed decisions by policymakers.

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3.1 Introduction

Developing effective policies to improve public health is challenging. The challenges are particularly acute in large, heterogeneous countries, and in settings where individuals engage in specific behaviors driven by diverse, complex, and often conflicting motivations. In such settings, 'one-size-fits-all' policies may not lead to optimal outcomes or achieve stated policy objectives. Therefore, policymakers would ideally want to account for such heterogeneity when developing and implementing policies.

Effective public health policy design is especially important when health risks and economic burden associated with the targeted behavior are substantial, as it is the case with tobacco consumption. In the United States, smoking is the leading cause of preventable deaths with 480,000 deaths each year (Lushniak et al., 2014). Furthermore, the U.S. annual economic burden of smoking − healthcare and labor market lost productivity costs − is estimated at USD 300 billion (Centers for Disease Control and Prevention, 2023a). Of relevance for public policy, these costs are borne by both smokers themselves (i.e., private costs) and non-smokers (i.e., external costs).[1]

The U.S. tobacco product market offers an excellent laboratory to examine the possible benefits of tailored public policy.[2] This market is complex and regulated by federal, state, and local governments, with significant variation across products in how strongly they are regulated. Moreover, there is an ongoing political debate on how to best regulate tobacco and smoking cessation products in the presence of heterogeneous preferences. The tobacco product market has changed considerably over the past decades with the emergence of e-cigarettes and the further development of smoking cessation medications. As a result, smokers can currently choose from a wide range of products varying in their health risks, out-of-pocket costs, and consumption experience. Smokers may further have diverse motivations for consuming these various products, which might also drive the heterogeneity in their preferences for specific tobacco products and product features. From a policy perspective, these developments complicate the understanding and predictability of smokers' behavior. The reasons behind preferring certain tobacco products may also have an effect on overall health, with some potentially improving health outcomes and others more likely worsening health. For instance, e-cigarette consumption may reduce adverse health effects if used as a substitute for tobacco cigarettes, while vaping potentially harms health if this behavior causes nicotine initiation, or if e-cigarettes are used as a complement to tobacco cigarettes (e.g., vaping where smoking is prohibited). In such settings,

[1] Smokers may experience internalities, regretting their earlier decision to smoke, which may also justify regulation (Gruber and Köszegi, 2001).

[2] This study focuses on the U.S. tobacco market, collecting preference data of U.S. adult smokers and selecting policy scenarios particularly interesting from an U.S. policy perspective. Nevertheless, our findings also inform policymakers of other countries and localities about smokers preferences and the potential effectiveness of various tobacco control policies.

the policymaker would want to tailor public health policy for such heterogeneity, incentivizing health-improving activities and disincentivizing others.

Ideally, policymakers could observe each individual's motives for the consumption of tobacco products and, based on this information, apply a different policy. However, tailoring policies at the individual level proves difficult in the real world.[3] Even tailoring public policy to different subgroups of the population is taxing conceptually, administratively, and politically. To date, this approach remains untested in most settings. Still, understanding and accounting for heterogeneity in individual behavior and motivations is crucial. Considering preference heterogeneity allows to better understand the often conflicting impacts policies have on different subpopulations, to identify potential unintended consequences, and to accurately assess the overall effectiveness of a policy. Moreover, the more detailed information may help mitigating the trade-off between encouraging health-improving behavior while discouraging health-worsening behavior.

In this study, we demonstrate the importance of accounting for preference heterogeneity and the implication of such heterogeneity for optimal health policy design using evidence from tobacco market regulations. We further fill the gap in the existing literature by (1) studying a more comprehensive set of products reflecting real-world choices; (2) identifying different smoker types through a latent class logit model and exploring their profiles using a rich set of background characteristics; and (3) predicting responses to currently discussed tobacco regulations in the United States. We first develop a conceptual framework for tobacco product demand. In this framework, we explicitly incorporate heterogeneity across smokers in terms of their preferences towards safety signals, addictive potential, out-of-pocket price, hassle costs, and other policy-relevant factors. Second, we use experimental data on 3,500 U.S. adult smokers obtained from a discrete choice experiment (DCE). The DCE method is widely used to quantify public preferences for various services, products, or interventions (De Bekker-Grob et al., 2012; Chandoevwit and Wasi, 2020; Mühlbacher and Johnson, 2016). Of particular relevance to our study, DCEs have been extensively used to explore tobacco product choice (Buckell et al., 2023; Marti et al., 2019; Pesko et al., 2016; Shang et al., 2020). Within our DCE, respondents are confronted with hypothetical choice situations mimicking complex real-world decision-making processes, encompassing multiple tobacco products. Across choice sets, we vary prices, nicotine content, prescription requirement (potentially signalling a product's safety or increasing hassle costs), and flavors of four tobacco and smoking cessation products (cigarettes, e-cigarettes, nicotine replacement therapies [NRTs], and non-nicotine smoking cessation medications [SCMs]). The DCE method allows the elicitation of preferences for multiple relevant product characteristics

[3]Nevertheless, tailoring at the individual level might be targeted in other domains such as precision medicine. Many health scholars see precision medicine as a pathway to achieve higher levels of well-being by exploiting differences in genetics, environment, lifestyle, and preferences across individuals (Ginsburg and Phillips, 2018; National Institutes of Health, 2024).

at once, and to predict smokers' responses to both widely adopted and newly discussed policies (Ryan et al., 2012). For instance, we study the preference for e-cigarettes sold as a medical product (i.e., requiring a prescription), and the smokers' responses to the prohibition of tobacco cigarettes with addictive nicotine levels; two proposed policies not yet introduced in the United States.

Our findings suggest that there is considerable preference heterogeneity among smokers, which is best described by four distinct types: *hardened smokers*, *e-cigarette-interested smokers*, *smoking-cessation-interested smokers*, and *opt-outs*. Therefore, considering the heterogeneous responses of different smoker types to tobacco control policies is crucial when developing new policies. The results further show that the majority of smokers have a strong attachment to a specific product type and are therefore relatively insensitive to tobacco policies targeting product attributes. Nevertheless, reducing nicotine in tobacco cigarettes to non-addictive levels appears to be an effective policy among all smokers.[4] Two smoker types, representing 38.2% of smokers, show potential responsiveness to further policies such as the prescription requirement for e-cigarettes and insurance coverage for smoking cessation products.

The remainder of this chapter is organized as follows. Section 3.2 provides information on the U.S. tobacco product market and develops a conceptual model for tobacco and smoking cessation product demand. The data and the design of the DCE are described in Section 3.3. Section 3.4 outlines the econometric approach to choice modelling and Section 3.5 presents our findings. Finally, we provide a discussion of the results and conclusions in Section 3.6.

3.2 Background

3.2.1 Tobacco products and regulation

In this section, we offer a brief description of the available tobacco and smoking cessation products, their risks, and the current regulatory landscape in the U.S. tobacco market. At one end of the risk continuum, combustible tobacco products (e.g., cigarettes, cigars, cigarillos, little cigars, and pipes) are arguably the most harmful to health (Lushniak et al., 2014). Using these combustible tobacco products, consumers must burn tobacco to activate the nicotine, the addictive ingredient in most tobacco products. The burning of tobacco releases carcinogens and other harmful toxicants that are inhaled by smokers. The federal government, all 50 states and DC, and various cities and counties across the U.S. impose taxes on cigarettes, with the median (mean) state tax in Q1 2023 being USD 1.78 (USD 1.92) per pack (Centers for Disease Control and Prevention, 2024). Some states and localities tax other combustibles. Furthermore,

[4]For the purposes of our study, a policy is considered effective if adopting the policy reduces the probability of choosing cigarettes and increases either the uptake rate of less harmful products or the probability of quitting.

smoking is banned in many worksites, restaurants, and bars. Sales of any tobacco product to those under the age of 21 are prohibited, with a federal minimum legal sales age implemented in December 2019 (Centers for Disease Control and Prevention, 2024).

Smokers have several alternative products available on the market that can be used either as a means to quit smoking or as a substitute source of nicotine. The Food and Drug Administration (FDA)[5] has approved seven smoking cessation products: five nicotine replacement therapies (NRTs) and two non-nicotine containing smoking cessation medications (SCM; Chantix [varenicline] and Zyban [buproprion]) (Centers for Disease Control and Prevention, 2021). Three of the five FDA-approved NRTs are available over-the-counter (gums, patches, and lozenges), but two NRTs (inhalers and nasal sprays) and both non-nicotine smoking cessation medications require a prescription from a healthcare professional. Several high-quality randomized controlled trials demonstrate the effectiveness of these products for smoking cessation. Relative to unassisted quitting, NRTs have been shown to increase quit rates by 50% to 60% (Hartmann-Boyce et al., 2018), buproprion increases quit rates by 80% and varenicline by 180% (Cahill et al., 2013).

Relatively recent tobacco products in the U.S. market are e-cigarettes, electronic devices with which the consumer inhales a vapor that typically contains nicotine, flavors, and other additives. These products, originally developed as a less harmful means of consuming nicotine for smokers, were first sold in the U.S. in 2006 (CASAA, 2023). Because no tobacco is burned, e-cigarettes are generally perceived by tobacco control experts as being less harmful to health than cigarettes and other combustible tobacco products (Allcott and Rafkin, 2022). Although there is substantial evidence that vaping is associated with considerably lower exposure to potentially toxic substances than smoking, Eaton et al. (2018) emphasize that e-cigarette use is associated with health risks and its long-term effects are uncertain. They further find evidence that vaping increases the risk of smoking initiation, especially among adolescents and young adults. Indeed, e-cigarettes have gained popularity in the United States. In 2021, 4.5% of adults reported current vaping, with this share being even higher among adolescents and young adults (11%) (Centers for Disease Control and Prevention, 2023b).

A study of Owusu et al. (2019) reveals that 41% of e-cigarette users report dual use of e-cigarettes and tobacco cigarettes. There are several distinct reasons for smokers to consume e-cigarettes. First, e-cigarettes can constitute a tool for harm reduction. Smokers may smoke less tobacco cigarettes, partially substituting tobacco cigarettes with e-cigarettes. Second, smokers might co-use the two products for purposes other than harm reduction. For instance, in Etter and Bullen (2011), 39% of smokers state that circumventing smoking bans is one reason for using e-cigarettes. Other consumers might simply enjoy vaping as a complement to smoking.

[5]The FDA is responsible for protecting the public health of U.S. residents by assuring the safety, efficacy, and security of human and veterinary drugs, biological products, medical devices, the nation's food supply, cosmetics, and products that emit radiation (United States Government, 2023). Of relevance to our study, the FDA has authority to regulate tobacco products at the federal level.

Third, e-cigarettes are increasingly used by smokers to quit nicotine (Rahman et al., 2015). In one survey, 24.6% of adults attempting to quit smoking fully substituted e-cigarettes for cigarettes (Caraballo et al., 2017). E-cigarettes may also be valuable for 'accidental quitters', smokers who may not be interested in traditional cessation methods, but who may turn to e-cigarettes in an informal or unplanned attempt to quit smoking (Kasza et al., 2021). A recent Cochrane Review found that e-cigarettes increased quit rates relative to NRTs by approximately four extra quitters per 100 (Hartmann-Boyce et al., 2022). However, fearing a relapse, most former smokers (79%), once switched, stick to vaping (Etter and Bullen, 2011).

Currently, e-cigarettes are available without a prescription in the United States, though the FDA must approve all commercial e-cigarettes. As of 2023, 30 states and DC, and several counties and cities tax e-cigarettes, but there is no federal e-cigarette tax (Centers for Disease Control and Prevention, 2024; Cotti et al., 2023). In the jurisdictions where e-cigarette taxes are implemented, these taxes are significantly lower than those on cigarettes (Cotti et al., 2023). Furthermore, only 45% of states apply indoor vaping restrictions, while 90% of states impose indoor smoking restrictions. Recently, several states and localities have prohibited the sales of flavored e-cigarettes (Public Health Law Center, 2023).

From a public policy perspective, there is a trade-off between the beneficial harm reduction for some smokers and the initiation or increase of tobacco product use among other (non-)smokers. Policymakers would want to promote the use of e-cigarettes among smokers that cannot quit otherwise and (partly) switch from cigarettes to e-cigarettes. In contrast, promoting vaping among non-smokers, smokers without a simultaneous reduction in smoking intensity, or among smokers that could fully quit smoking without the help of e-cigarettes is not a policy objective. Hence, there are ongoing political debates on the need, design, and potential effectiveness of further e-cigarette regulations and tobacco market regulations in general. Recently, the FDA has proposed limiting the amount of nicotine contained in tobacco products to extremely low levels as a means to reduce addiction (Food and Drug Administration, 2022). Another policy currently discussed in the U.S. is the introduction of a prescription requirement for e-cigarettes. This approach would restrict the access to e-cigarettes for non-smokers and smokers that use e-cigarettes as a commercial product, while promoting the use of e-cigarettes as a smoking cessation tool.

3.2.2 Conceptual framework

Our conceptual framework is based on the demand for nicotine outlined by Lillard (2020). We adapt the Lillard model to our setting, incorporating recent evidence on tobacco consumption and smokers' behavior (see e.g., Buckell et al., 2021; Buckell et al., 2023; Marti et al., 2019). A key contribution of Lillard (2020) is formalizing that demand for tobacco products is derived

from consumer's demand for nicotine. Whereas Lillard (2020) includes a comprehensive set of nicotine-containing tobacco products, we focus on combustible cigarettes, e-cigarettes, and NRTs.[6] Additionally, our framework includes non-nicotine options: SCMs and unassisted quitting. Consumers may demand SCMs or choose to quit unassisted as a means to avoid nicotine along with harmful ingredients in tobacco products.

In the economic literature, the demand for tobacco products is usually derived based on the assumption that individuals maximize their utility when deciding whether, how much and which tobacco products to consume (see e.g., Becker and Murphy, 1988; Buckell et al., 2023; Lillard, 2020; Marti et al., 2019).[7] We follow this convention and rely on the random utility maximization (RUM) theory to derive demand for different tobacco and smoking cessation products (McFadden, 1974). Specifically, RUM assumes that each consumer chooses the tobacco or smoking cessation product out of a set of available alternatives that provides the highest utility (see Section 3.4.1 for more details on RUM). In our setting, utility is a function of the experienced benefit and the health consequences from consuming tobacco and smoking cessation products. The experienced benefit depends on nicotine content, flavor, and inherent product utility. In addition to nicotine, as suggested by Lillard (2020), flavor is included as a component of experienced benefit because previous studies have shown that flavors significantly influence the individual's vaping experience (see e.g., Buckell and Sindelar, 2019; Czoli et al., 2016). The inherent product utility, measured by product-specific constants in our model, captures unobserved addiction, habitual product use, and subjective risk perceptions. In terms of health consequences, we assume that e-cigarettes, NRTs and SCMs have lower adverse health effects than continuing to smoke cigarettes.[8] As we do not vary health-related attributes in our experiment, these features are captured by product-specific constants in our empirical specification.

Furthermore, the consumer's decision is a constrained maximization problem as smokers cannot consume more than allowed by their available resources. Following Lillard (2020), we additionally consider shadow prices of tobacco and smoking cessation products. Shadow prices incorporate both health consequences and social desirability (or lack thereof) associated with consuming a specific product. In our setting, we emphasize financial, hassle, and social desirability costs. We use dollar values and the notion of insurance coverage to capture financial prices, and requiring a prescription to proxy hassle and social desirability costs. Higher dollar prices per product and lower insurance coverage unambiguously increase financial out-of-pocket costs. In contrast, requiring a prescription can potentially increase or decrease hassle costs de-

[6] In particular, snuff, snus, cigarillos, etc. are not part of our study.

[7] Lillard (2020) assumes that consumers maximize a lifetime utility function, whereby our study is cross-sectional. We therefore modify the framework to a one-period model.

[8] As stated, smoking tobacco cigarettes requires the inhalation of carcinogens and other toxicants, which has shown to be the most harmful in the literature (see e.g., Eaton et al., 2018).

pending on consumer preferences. A prescription requires a consultation with a healthcare professional, which can increase the hassle costs for consumers.[9] On the other hand, prescriptions may signal product safety because a healthcare professional is suggesting its use or reduce social desirability costs because the product may be viewed as a medicine rather than a 'sin good.'[10]

Previous studies have shown the importance of considering heterogeneous preferences among the consumers of tobacco products (see e.g., Buckell et al., 2023; Marti et al., 2019; Paterson et al., 2008). We therefore allow for the direction and magnitude of an attribute's effect on smokers' utility to vary between different types of smokers. For instance, the product attachment and the preference for nicotine is allowed to vary between groups of more and less addicted smokers as suggested by Buckell et al. (2021).

Our conceptual framework offers several testable predictions which we outline in Table 3.1. We test these predictions using the data and methods described in Section 3.3 and 3.4, and we discuss the extent to which our data supports these predictions in Section 3.5.3.

Table 3.1: Predictions on the behavior of smokers

Prediction 1	Increasing the (financial) price of a product (due to an increase in the dollar price or decrease in insurance coverage) will reduce the quantity demanded of this tobacco and smoking cessation product.
Prediction 2	Increasing the hassle cost, proxied by requiring a prescription from a healthcare professional to obtain e-cigarettes, could decrease the quantity demanded. However, if a prescription signals product safety to consumers, and safety increases utility, than requiring a prescription may increase demand for some consumers.
Prediction 3	Prohibiting flavors will decrease the utility experienced from consuming e-cigarettes and will decrease demand among smokers that prefer flavored e-cigarettes.
Prediction 4	Removing nicotine should reduce the experienced benefits of consuming cigarettes, and thus reduce demand.

Note: This table presents predictions on the behavior of smokers derived from our conceptual framework. These predictions are tested and further discussed in Section 3.5.3.

[9]It may also increase the financial price for uninsured patients and, through cost-sharing, potentially also insured patients.

[10]Note that, similarly, insurance coverage of a product might also signal the product's safety or its social desirability. Nevertheless, as potential signalling effects and price incentives point into the same direction, we abstract from safety and social desirability signals in interpreting the "price sensitivity" estimates of NRTs and SCMs but keep in mind that those estimates might be partly driven by positive signalling.

3.3 Data

3.3.1 Data collection and survey design

To analyze smokers' preferences and to test the predictions outlined in Table 3.1, we use a discrete choice experiment (DCE). Respondents, all adult smokers in the U.S., are presented with hypothetical choice situations and asked to choose among four alternative tobacco and smoking cessation products and unassisted quitting, which serves as the opt-out option. We programmed the survey in Qualtrics software and conducted the survey online between February and March 2023. Qualtrics is a common platform for online surveys in economics (see e.g., Charness et al., 2022; Elías et al., 2019; Marti et al., 2019). We include over 3,500 completed surveys with a sample representative of the U.S. smokers population based on sex, age, education, and region. We use the 2021 Behavioral Risk Factor Surveillance Survey (BRFSS), a large and nationally representative survey conducted by the Centers of Disease Control and Prevention, to benchmark our sample (Mokdad, 2009). Our survey consists of three main sections: (1) a general introduction and collection of background information, (2) the experimental component (labeled DCE), and (3) follow-up questions on smoking and vaping habits, health, income, political views, race, ethnicity, and subjective smoking and vaping risk perceptions. At the beginning of the DCE section, detailed instructions and descriptions of the considered products and their attributes with all possible attribute levels are provided to the respondents. Additionally, we show the respondents an example of a choice set that explains the options to ensure that they understand the survey. Each respondent has to complete eight main choice tasks, together with one practice and one test-retest task to asses response quality (Pearce et al., 2021).[11] The estimated completion time was 15 minutes.

We use a labeled DCE design, making the choice options more realistic and cognitively recognizable for the respondents, whereby the individual feelings or beliefs about the product type can be accounted for.[12] Especially for products with addictive potential that foster consumer loyalty, such an approach mirrors the real-world experiences and can enhance the validity of the results (De Bekker-Grob et al., 2010; Buckell and Sindelar, 2019). Within our labeled DCE, we ask smokers to consider a three-month time horizon and to indicate their choice between cigarettes, e-cigarettes (refillable vaping pens), prescription SCM (Chantix), over-the-counter NRT (gum), and unassisted quitting.[13] Unassisted quitting is added to the choice task to avoid overestimating the demand for potential alternatives to cigarettes (i.e., e-cigarettes, NRTs or

[11] Further details on the development of the DCE and the assessment of the design quality are provided in Section 3.A.1

[12] In an unlabeled DCE design, the options would not be presented with the product label but with a generic label (e.g., "Product A").

[13] We ask respondents to consider a three-month horizon to strike a balance between long-term habits, which are difficult to predict, and short-term decisions.

SCM). An example of an online choice task is presented in Figure 3.1. We include four product attributes – prescription requirement, flavor, out-of-pocket price, and nicotine – that can be manipulated by regulators and are thus particularly important from a policy perspective. We focus on attributes that are widely used in similar studies: price, nicotine level, flavors (see e.g., Buckell and Sindelar, 2019; Buckell et al., 2020; Cotti et al., 2022; Hoek et al., 2022; Maclean et al., 2019; Marti et al., 2019). Furthermore, the motivation to analyze various pol-

Figure 3.1: Choice task example

Which of the following products are you most likely to use three months from now?

	Cigarettes	Vape pen (refillable)	NRT (gum)	Drug (Chantix)	I will quit smoking on my own
					
Prescription required	No	No	No	Yes	
Flavor	Original (tobacco)	Menthol only	None	None	
Daily price	$9	$4, incl. tax Starter kit:$35	$6 (no insurance coverage)	$0 (with 100% insurance coverage)	
Nicotine level	Low (6 mg, 50% less)	Low (1.5 mg, 50% less)	Regular (4 mg)	None	

Note: This figure shows an example choice task as presented to the respondents in the discrete choice experiment. Respondents are asked to choose among four alternative tobacco and smoking cessation products, and an opt-out option (unassisted quitting). We use actual product labels, revealing to the respondent which option refers to which tobacco or smoking cessation product. Each respondent answers eight choice tasks. The levels of the four considered product attributes (prescription requirement, flavor, price, and nicotine content) are varied across choice tasks.

icy scenarios, which are currently proposed, but not yet implemented in the U.S., leads us to additionally include prescription requirement for e-cigarettes and the notion of health insurance coverage within the price of smoking cessation products (i.e., NRT and SCM). The four attributes and their levels are presented in Table 3.2. For e-cigarettes, we also show the upfront costs for the device (USD 35) in the DCE, but we do not vary these starter kit costs across choice tasks. Limiting to four attributes out of all potentially important attributes of tobacco and smoking cessation products ensures that choice tasks remain cognitively manageable for the respondents. A concern with an overly complex choice set is that respondents may rely on heuristics in their decision-making process rather than carefully assessing all presented attribute levels when comparing the products (Payne, 1976; Swait and Adamowicz, 2001). The selected levels represent the current market conditions and regulations, and potential changes under discussion. Specifically, for the price attribute, the prices of all products are anchored to a comparable unit, which is equal to smoking a pack of 20 cigarettes (Cheng et al., 2021; Liber

et al., 2017). For a detailed description on the selection of attribute levels, we refer to Section 3.A.2 in the Appendix.

Table 3.2: DCE Design and chosen attribute levels

	Cigarettes	**E-cigarettes**	**NRT (gum)**	**SCM (Chantix)**	**Unassisted quitting**
Daily OOP costs (USD)	9	4 (with tax), 4 (no tax) 6 (with tax), 6 (no tax) 8 (with tax), 8 (no tax)	0 (100% ins. cov.) 3 (50% ins. cov.) 6 (no ins. cov.)	0 (100% ins. cov.) 4.5 (50% ins. cov.) 9 (no ins. cov.)	- -
Prescription	No	Yes, No	No	Yes, No	-
Nicotine	Regular (12mg) Low (6mg, -50%) Very low (0.6mg, -95%)	Regular (3mg) Low (1.5mg, -50%) Very low (0.15mg, -95%)	Regular (4mg)	None	-
Flavor	Original (tobacco)	Various (fruit, candy,...) Menthol Flavor No Flavor	None	None	-

Note: This table presents the attribute levels used in the choice tasks. By varying the levels of the attributes across choice taks, the DCE method allows to elicit the respondents' preferences for these attributes. Note that not all attributes are varied for all the alternatives and that possible levels differ across alternatives. The definition of attribute levels is based on previous studies, current market availabilities, and proposed policies. The abbreviation *OOP costs* stands for out-of-pocket costs. For e-cigarettes, we additionally show the costs for the starter kit (USD 35) along with the variable out-of-pocket costs, but we do not vary these upfront costs across choice tasks.

3.3.2 Sample characteristics

Table 3.5 (column 1 "Overall") shows the descriptive statistics on our final sample. We reached 3,433 completed responses of U.S. smokers aged 21−64 years, residing in all states across the United States. The average age of smokers in our sample is 45.6 years. The majority of respondents are employed (63.2%), hold at least a high-school education (94.4%), and have health insurance (87.4%). Most respondents smoke cigarettes every day (86%). The majority of respondents (79%) have tried e-cigarettes at some point, while only 12.4% use e-cigarettes daily. Almost half of the smokers state that they have tried to quit smoking at least once within the past twelve months. On average, respondents estimate the risk of dying from smoking-related illnesses to be higher than risks associated with vaping. Nevertheless, 57.8% of respondents consider vaping to be at least as risky as smoking. This suggests that smokers may have inaccurate assessments of health risks associated with the use of these two product types (Allcott and Rafkin, 2022). The median time for completion of the survey is 8.62 minutes and 76.6% of respondents demonstrate consistent choice behavior.[14]

[14]The consistency of choice behavior is measured by comparing the respondents' choices in the test and the retest task which represent exactly the same choice situation. As a robustness check, we show the estimation results using only the observations of consistent respondents in Table 3.B.1 in the Appendix.

3.4 Econometric approach to choice modelling

This section outlines the econometric approach we utilize. More specifically, we discuss the estimation of taste parameters and the simulation of product uptake rates (choice probabilities) in various policy scenarios.

3.4.1 Estimation of taste parameters

Our analyses are based on the conceptual framework developed in Section 3.2.2. As stated, we use the RUM framework to estimate preferences (McFadden, 1974). Specifically, we assume that each respondent i chooses in repeated choice tasks $t = (1, ..., 8)$ the product j among five alternatives (cigarette, e-cigarettes, NRT, SCM, unassisted quitting) to maximize her utility U_{ijt}. In the parametric version of the RUM, Equation (3.1), utility is comprised of a deterministic part consisting of observable product attributes, V_{ijt}, and an unobservable part represented by a stochastic error term, ϵ_{ijt}. Thus, this framework enables the researcher to link observed product choices to the attributes of the available products (Hess et al., 2018).

$$U_{ijt} = V_{ijt} + \epsilon_{ijt} \tag{3.1}$$

In our setting, we specify the representative utility, V_{ijt}, for each product j, as a linear function of a product constant (referred to as alternative-specific constant; or ASC), and the product attributes reported in Table 3.2. Some attributes are only varied for a subset of alternatives. Consequently, those attributes only enter the representative utility for alternatives for which there is variation in the attribute level.

$$V_{cig,it} = ASC_{cig} + \beta_{cig,low} Nic\_low_{ijt} + \beta_{cig,vlow} Nic\_vlow_{ijt} \tag{3.2}$$

$$\begin{aligned} V_{ecig,it} = ASC_{ecig} + \beta_{ecig,p} Price_{ijt} + \beta_{ecig,presc} Prescr_{ijt} + \beta_{ecig,low} Nic\_low_{ijt} + \\ \beta_{ecig,vlow} Nic\_vlow_{ijt} + \beta_{noflav} Noflav_{ijt} + \beta_{menthol} Menthol_{ijt} + \beta_{tax} Tax_{ijt} \end{aligned} \tag{3.3}$$

$$V_{nrt,it} = ASC_{nrt} + \beta_{nrt,p} Price_{ijt} \tag{3.4}$$

$$V_{scm,it} = ASC_{scm} + \beta_{scm,p} Price_{ijt} + \beta_{scm,presc} Prescr_{ijt} \tag{3.5}$$

$$V_{optout,it} = ASC_{optout} \tag{3.6}$$

We normalize ASC_{optout} to zero such that the preference for the product types (regardless of attributes) are measured relative to the opt-out option (unassisted quitting). The prices of e-cigarettes, NRTs and SCMs are measured relative to the price of cigarettes, which is

fixed at USD 9 across all choice tasks. Using separate price coefficients for the relative prices of e-cigarettes, NRTs, and SCMs allows the price sensitivity to vary across products. The potential disutility of non-flavored and only-menthol-flavored e-cigarettes is estimated relative to the reference of having various e-cigarette flavors available. Similarly, we use regular nicotine content as the reference category to measure potential disutilities of low and very low nicotine content in cigarettes and e-cigarettes.

As a starting point, we use a conditional logit (CL) model to estimate the taste parameters, β, representing smokers' preferences. The basic CL model is the workhorse in choice modelling and assumes a single utility function for all respondents, imposing homogeneous preferences for tobacco and smoking cessation products (see e.g., Train, 2009, for details on the method). Given that our primary objective is to analyze heterogeneous preferences among various smoker types, we use the results from the CL estimation solely as a baseline for comparison. In particular, this comparison reflects the potential inaccuracies the CL model yields when applied to diverse populations, providing policymakers with an oversimplified picture of population preferences.

In a second step, we extend the CL framework and model preference heterogeneity in a latent class logit (LCL) model (see e.g., Bhat, 1997; Pacifico and Yoo, 2013; Train, 2009). Previous studies widely use LCL to identify smokers' preferences and to predict their behavior (see e.g., Buckell et al., 2023; Marti et al., 2019). This model assumes that there exist C relatively homogeneous classes of smokers, within which respondents have similar preferences and make choices consistent with their class-specific CL model. Put differently, the LCL model employs an iterative, data-driven approach to identify groups of smokers with similar stated preferences and to estimate a distinct taste parameter vector β for each class. Moreover, we model class membership probabilities as a function of age, family income, education, health insurance, smoking and vaping habits, and smoking and vaping risk perceptions. Predicting class membership in this manner allows us to illustrate the distinct profiles of smokers observed within the classes. We refer to Section 3.A.3 in the Appendix for details on the estimation method.

To perform the maximum likelihood estimations, we use the R package *apollo*, Version 0.3.0 (Hess and Palma, 2019). To account for the panel structure of the data, the software employs robust standard errors clustered at the individual level. Based on the common choice behavior detected within the classes, we ex-post assign a label to each class. Since the model requires specifying the number of classes empirically, we opt for four classes. This choice is made to trade-off optimal model fit (based on BIC and AIC) and interpretability of results.

3.4.2 Policy scenario simulations

The aim of our policy scenario simulation is to explore whether, and to what extent, tobacco policies targeting product attributes can trigger changes in smokers' choices. For this pur-

pose, we construct policy scenarios potentially decreasing the attractiveness of cigarettes while increasing the attractiveness of alternative smoking cessation options (see Table 3.C.2 in the Appendix for a detailed description of the chosen policy scenarios). As the reasons and consequences of e-cigarette use are complex, we model restrictive e-cigarette policies possibly leading smokers to switch back to cigarettes (e.g., flavor bans, hassle costs associated with prescription requirement for e-cigarettes), but we also model policies potentially motivating smokers to switch to the less harmful NRTs and SCMs (e.g., insurance coverage for these products). Moreover, we study whether for some smokers the positive signalling of e-cigarette prescription outweighs the associated hassle costs. We focus on single-action policies in the main part of the paper for brevity, and show results on multiple-actions policies in the Appendix.

Using the estimated taste parameters $\hat{\beta}$, we can predict uptake rates (choice probabilities) of products with certain features x_{sj} based on the following equation:

$$\hat{P}_{cs}(j) = \frac{exp(V_{jcs})}{\sum_{k=1}^{J} exp(V_{kcs})} = \frac{exp(\boldsymbol{x'_{js}}\hat{\boldsymbol{\beta}}_{\boldsymbol{c}})}{\sum_{k=1}^{J} exp(\boldsymbol{x'_{ks}}\hat{\boldsymbol{\beta}}_{\boldsymbol{c}})} \tag{3.7}$$

where $\hat{P}_{cs}(j)$ is the estimated probability to choose product j with specific attribute levels $\boldsymbol{x_{js}}$ for smokers in class c. Allowing for preference heterogeneity in the LCL model results in a set of conditional choice probabilities, one for each class c and product j based on the class-specific taste parameters $\hat{\boldsymbol{\beta}}_{\boldsymbol{c}}$. For predictions assuming homogeneous preferences (CL model), we get a single choice probability for each product j. To simulate different policy scenarios, we vary the vector of attribute levels $\boldsymbol{x_{js}}$ according to the definition of the corresponding scenario s.[15]

For the comparison of the CL and the LCL predictions, we aggregate the class-specific choice probabilities in the LCL model at the population level using the estimated class shares, $\hat{\pi}_c$, as respective weights:

$$\hat{P}_s(j) = \sum_{\forall c \in C} \hat{\pi}_c \hat{P}_{cs}(j) \tag{3.8}$$

We then compute the change in the predicted choice probability for each product under a policy scenario s relative to its status quo choice probability: $\tilde{P}_s(j) = \hat{P}_s(j) - \hat{P}_{statusquo}(j)$. The status quo represents choice probabilities for attribute levels at current prices and current regulatory landscape in the United States (see Table 3.C.2 for details).

Finally, we study the class-specific changes in choice probabilities ($\tilde{P}_{cs}(j) = \hat{P}_{cs}(j) - \hat{P}_{c,statusquo}(j)$) in response to various policy scenarios to assess the effectiveness of these policies among distinct smoker types and to identify potential unintended consequences among subgroups of smokers.

[15]For instance, for predicting choice probabilities under the prescription requirement for e-cigarettes, we switch the value for prescription requirement to one for the e-cigarette alternative.

3.5 Results

3.5.1 Smokers preferences and heterogeneity analysis

The estimated taste parameters in Table 3.3 reveal that smokers have a strong attachment to specific product types. The estimated product constants (ASCs), reflecting the product types, are highly significant and large (in absolute value) compared to taste parameters for product attributes, in both the CL model and the class-specific estimates of the LCL model. This suggests that smokers highly value product types and pay limited attention to specific attributes of a product.

Table 3.3: Taste parameter estimates: conditional logit and latent class logit

	CL	**Class 1**	**Class 2**	**Class 3**	**Class 4**
ASC: Cigs	1.758***	4.178***	2.041***	0.954***	-1.676***
	(0.055)	(0.138)	(0.193)	(0.192)	(0.193)
ASC: SCM (Chantix)	-0.114.	-0.66*	0.139	2.129***	-3.046***
	(0.066)	(0.282)	(0.263)	(0.182)	(0.406)
ASC: E-cigs	0.604***	0.31	3.104***	1.19***	-2.588***
	(0.083)	(0.341)	(0.22)	(0.275)	(0.665)
ASC: NRT (gum)	-0.134*	-0.576*	0.575**	2.036***	-3.14***
ASC: Unassisted quitting	ref. group				
Prescription to obtain SCM	0.048	-0.171	0.105	0.062	0.093
	(0.037)	(0.209)	(0.178)	(0.055)	(0.283)
Pescription to obtain e-cigs	0.02	0.111	-0.11.	0.318**	0.144
	(0.03)	(0.138)	(0.063)	(0.109)	(0.273)
Nicotine level cigs: Regular (12mg)	base level				
Nicotine level cigs: Low (6mg)	-0.001	-0.153	0.028	-0.1	-0.055
	(0.038)	(0.119)	(0.092)	(0.126)	(0.157)
Nicotine level cigs: Very low (0.6mg)	-0.11*	-0.423**	-0.072	-0.271.	-0.271
	(0.052)	(0.133)	(0.12)	(0.161)	(0.216)
Nicotine level e-cigs: Regular (3mg)	base level				
Nicotine level e-cigs: Low (1.5mg)	-0.089*	-0.472*	-0.07	-0.2.	0.313
	(0.039)	(0.197)	(0.073)	(0.122)	(0.258)
Nicotine level e-cigs: Very low (0.15mg)	-0.025	-0.127	-0.044	-0.036	-0.037
	(0.033)	(0.166)	(0.074)	(0.128)	(0.305)
Relative price for SCM	-0.338***	-0.163	-0.422.	-0.51***	-0.473
	(0.05)	(0.322)	(0.248)	(0.081)	(0.382)
Relative price for NRT gum	-0.461***	-0.498	-0.021	-0.764***	-0.807
	(0.077)	(0.446)	(0.217)	(0.125)	(0.897)
Relative price for e-cigs	-0.187*	-0.149	-0.158	-0.709*	-0.596
	(0.078)	(0.366)	(0.162)	(0.296)	(0.612)
Price for e-cigs includes tax	0.049	-0.034	0.125*	-0.064	-0.166
	(0.032)	(0.139)	(0.061)	(0.102)	(0.211)
E-cigarettes with various flavors	base level				
E-cigs with menthol flavor	-0.048	-0.036	-0.095	-0.071	-0.259
	(0.036)	(0.161)	(0.071)	(0.11)	(0.27)
E-cigs with no flavor	-0.043	0.011	-0.109.	-0.096	-0.148
	(0.032)	(0.158)	(0.062)	(0.108)	(0.288)

Note: This table presents the estimated taste parameters from the conditional logit model (CL) in the first column and the class-specific taste parameter estimates from the latent class logit (LCL) model with four classes in column two to five. The R-package *apollo* is used for estimation. We employ robust standard errors clustered at the individual level. The estimation is performed on the final sample with 3,433 respondents and 27,464 observations (eight choice tasks each).

Table 3.3 (columns 2-5, presenting the results of the LCL model) confirms the presence of considerable heterogeneity in smokers' preferences. Distinct subgroups of smokers value product types and product attributes differently.[16] Because smokers' preferences are more nuanced, imposing homogeneous preferences in the CL model results in biased estimates (Table 3.3, column 1). First, the CL model might underestimate the relative importance of product attributes if different smoker types have opposite utility for this attribute (e.g., prescription requirement for e-cigarettes). In this case, opposing effects might cancel each other out if we do not allow for preference heterogeneity. Consequently, and concerningly from the perspective of the policymaker, we might wrongly conclude that the attribute does not impact smokers' choices. Second, and specifically in our setting with very strong product attachment, the fact that distinct smoker types favor different products cannot be represented in one single vector of product constants. Therefore, accounting for heterogeneity in smokers' preferences is crucial to obtain unbiased estimates of smokers' valuation of product attributes. In Section 3.5.3, we briefly discuss the implications of ignoring preference heterogeneity in policy scenario simulation and for deriving policy recommendations.

Henceforth, we focus on the results of the LCL estimation and describe the identified types of smokers and their preferences based on Table 3.3 and Table 3.4.[17] The majority of smokers (class 1, 51.8%) have a strong preference for cigarettes, choosing cigarettes in 94.6% of the choice tasks (see Table 3.4). We therefore label them *'hardened' smokers*. The large and highly

Table 3.4: Observed choice shares: overall and by class

	Overall	**Class 1**	**Class 2**	**Class 3**	**Class 4**
Choice shares					
Cigarettes	57.7%	94.6%	25.1%	12.6%	13.3%
E-cigarettes	16.1%	1.94%	62.6%	11.3%	3.59%
NRT (gum)	7.82%	0.892%	5.76%	33.1%	2.53%
SCM (Chantix)	8.05%	0.780%	3.28%	37.3%	2.93%
Unassisted quitting	10.3%	1.76%	3.34%	5.64%	77.6%
Relative class size	-	51.8%	20.3%	17.9%	9.93%
Label	-	Hardened smokers	E-cigarette-interested smokers	Smoking-cessation-interested smokers	Opt-outs

Note: This table shows the choice shares of all tobacco and smoking cessation products and unassisted quitting across all choice tasks, overall and by smoker type identified in the LCL model. Based on the class-specific choice behavior observed, we assign a label to each class/smoker type.

[16] Figure 3.B.2 in the Appendix, presenting each attributes' importance for the smokers' choices further illustrates the strong attachment to product types and the heterogeneity in preferences between different types of smokers.

[17] The class-specific preferences for product attributes can be derived from the taste parameter estimates in Table 3.3, while the observed class-specific choice shares are depicted in Table 3.4.

significant product constant for cigarettes, depicted in Table 3.3, suggests that this smoker type prefers cigarettes regardless of most product attributes. Hardened smokers appear only sensitive to nicotine levels in cigarettes and e-cigarettes, disliking lower nicotine content. One fifth of smokers (class 2) predominantly chooses the e-cigarette (62.6%) or cigarette option (25.1%). We therefore label them *'e-cigarette-interested' smokers*. E-cigarette-interested smokers prefer flavored e-cigarettes and dislike prescription e-cigarettes. They are somewhat sensitive to the price of SCMs, but less to the prices of e-cigarettes and NRTs. According to Table 3.4, 17.9% of smokers (class 3) most often opt for smoking cessation products (NRT or SCM). Therefore, we label them *'smoking-cessation-interested' smokers*. Table 3.3 reveals that requiring a prescription increases the probability of choosing e-cigarettes for this group. Smoking-cessation-interested smokers are sensitive to the prices of all products. Moreover, lower nicotine levels in cigarettes and e-cigarettes negatively impact their utility. Finally, the remaining subgroup of smokers (class 4, 9.93%) is labeled *'opt-outs'*, as they choose consistently the option to quit unassisted (77.6%) regardless of most product attributes.

3.5.2 Profile of smoker types

The class-specific descriptive statistics in Table 3.5 offer suggestive evidence that the stated preferences can be explained, to some extent, by the respondents' actual smoking and vaping behavior at the time of completing the survey. For instance, 94.1% of hardened smokers smoke every day, only a small share (5.9%) use e-cigarettes frequently, and the majority of hardened smokers (69.3%) do not use e-cigarettes at all. Hardened smokers further display higher levels of nicotine addiction, with a considerably higher share of individuals smoking their first cigarette within five minutes of waking up. Moreover, hardened smokers are less likely to have tried to quit smoking in the past twelve months.

In contrast, one-third of e-cigarette-interested smokers, who demonstrate a strong preference for e-cigarettes, reports daily vaping. Furthermore, e-cigarette-interested smokers more often perceive vaping as less risky than smoking. Vaping appears to be more popular among younger smokers as the lower average age within the class of e-cigarette-interested smokers suggests. In addition, e-cigarette-interested and smoking-cessation-interested smokers are on average more educated, more often employed, and earn higher income than the classes of hardened smokers and opt-outs.

Smoking-cessation-interested smokers are characterized by a higher share of daily smokers than e-cigarette-interested smokers and opt-outs. However, smoking-cessation-interested smokers are also most likely to have tried to quit smoking in the past twelve months (62.8%). More than 50% of smoking-cessation-interested smokers use e-cigarettes at least occasionally.

Opt-outs appear to be the least nicotine-dependent group, as evidenced by smoking their first

Table 3.5: Background characteristics: overall and by class

	Overall	**Class 1**	**Class 2**	**Class 3**	**Class 4**
N (%)	3,433 (100)	1,779 (51.8)	697 (20.3)	616 (17.9)	341 (9.93)
Individual Characteristics					
Age, mean (sd)	45.6 (11.4)	47.1 (10.9)	40.3 (10.9)	45.0 (11.5)	48.8 (11.4)
Female, N (%)	1,728 (50.3)	927 (52.1)	325 (46.6)	305 (49.5)	171 (50.2)
Employed, N (%)	2,171 (63.2)	1,039 (58.4)	537 (77.0)	420 (68.2)	175 (51.3)
Unemployed, N (%)	269 (7.84)	155 (8.71)	36 (5.16)	42 (6.82)	36 (10.6)
Low educ. (below high-school), N (%)	193 (5.62)	114 (6.41)	20 (2.87)	19 (3.08)	40 (11.7)
Has health insurance, N (%)	3,001 (87.4)	1,519 (85.4)	621 (89.1)	577 (93.7)	284 (83.3)
Smoking Habits, N (%)					
Daily smoker	2,953 (86.0)	1,674 (94.1)	530 (76.0)	509 (82.6)	240 (70.4)
First cig < 5min after wake up	1,253 (36.5)	759 (42.7)	217 (31.1)	200 (32.5)	77 (22.6)
First cig 6-60min after wake up	1,840 (53.6)	888 (49.9)	404 (58.0)	362 (58.8)	186 (54.6)
First cig > 60min after wake up	340 (9.90)	132 (7.42)	76 (10.9)	54 (8.77)	78 (22.9)
Past quit attempt	1,610 (46.9)	602 (33.8)	424 (60.8)	387 (62.8)	197 (57.8)
Vaping Habits, N (%)					
Ever tried e-cigarettes	2,713 (79.0)	1,306 (73.4)	670 (96.1)	511 (83.0)	226 (66.3)
Daily vaper	425 (12.4)	105 (5.90)	242 (34.7)	62 (10.1)	16 (4.69)
No e-cigarette use	1,877 (54.7)	1,232 (69.3)	99 (14.2)	290 (47.1)	256 (75.1)
Subjective Risk Perception					
Smoking risk perc., mean (sd)	44.2 (24.3)	43.4 (24.7)	43.8 (23.9)	46.0 (22.7)	45.8 (26.7)
Vaping risk perc., mean (sd)	42.1 (26.0)	43.5 (26.2)	37.0 (24.5)	42.9 (25.9)	45.3 (28.1)
Vaping equally / more risky, N (%)	1,985 (57.8)	1,111 (62.5)	291 (41.8)	373 (60.6)	210 (61.6)
Data quality					
Completion time in min., median (iqr)	8.62 (5.97)	8.43 (5.78)	8.45 (5.82)	9.15 (6.63)	9.15 (6.08)
Consistent answers, N (%)	2,629 (76.6)	1,596 (89.7)	409 (58.7)	363 (58.9)	261 (76.5)

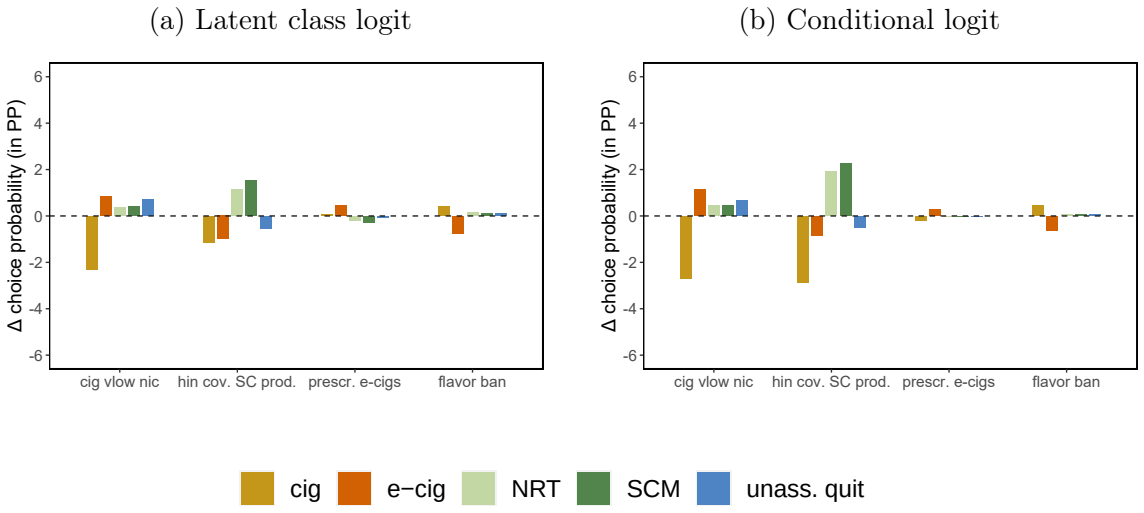
Note: The table presents descriptive statistics for the full sample and separately by the smoker types identified in the latent class logit model. N = Number of respondents. Average perceived smoking and vaping risks are calculated excluding missings (20% and 27% of observations, respectively). For a description of the variables, we refer to Appendix Table 3.C.1.

cigarette, on average, the latest after waking up. Unemployment is highest among the opt-outs, while educational attainment is lowest. The coefficient estimates for class membership probabilities in the LCL model (see Table 3.C.3 in the Appendix) support the sign and significance of these descriptive differences in background characteristics between the different smoker types.

3.5.3 Policy scenario analyses

Given that different smoker types demonstrate heterogeneous preferences for tobacco and smoking cessation products and their attributes, they potentially react differently to tobacco policies. We simulate the changes in choice probabilities of the four tobacco and smoking cessation products and quitting in response to the policy scenarios described in Appendix Table 3.C.2. In a first step, we study these predicted changes in smokers' product uptake on the population aggregate. Figure 3.2a shows the aggregated predictions from the LCL model as described in Section 3.4.2 (Equation (3.8)). The figure reveals that, overall, responses to policies are limited. Based on our results, the only somewhat effective policy is the reduction of nicotine in cigarettes to very low and potentially non-addictive levels. This policy is estimated to reduce the uptake of cigarettes by approximately 2.3 percentage points (or 4.0%). Comparing the predictions from the LCL model in 3.2a and the predictions from the CL model in 3.2b indicates that the CL model clearly overestimates the effectiveness of introducing health insurance coverage for smoking cessation products.

Figure 3.2: Policy scenario simulations

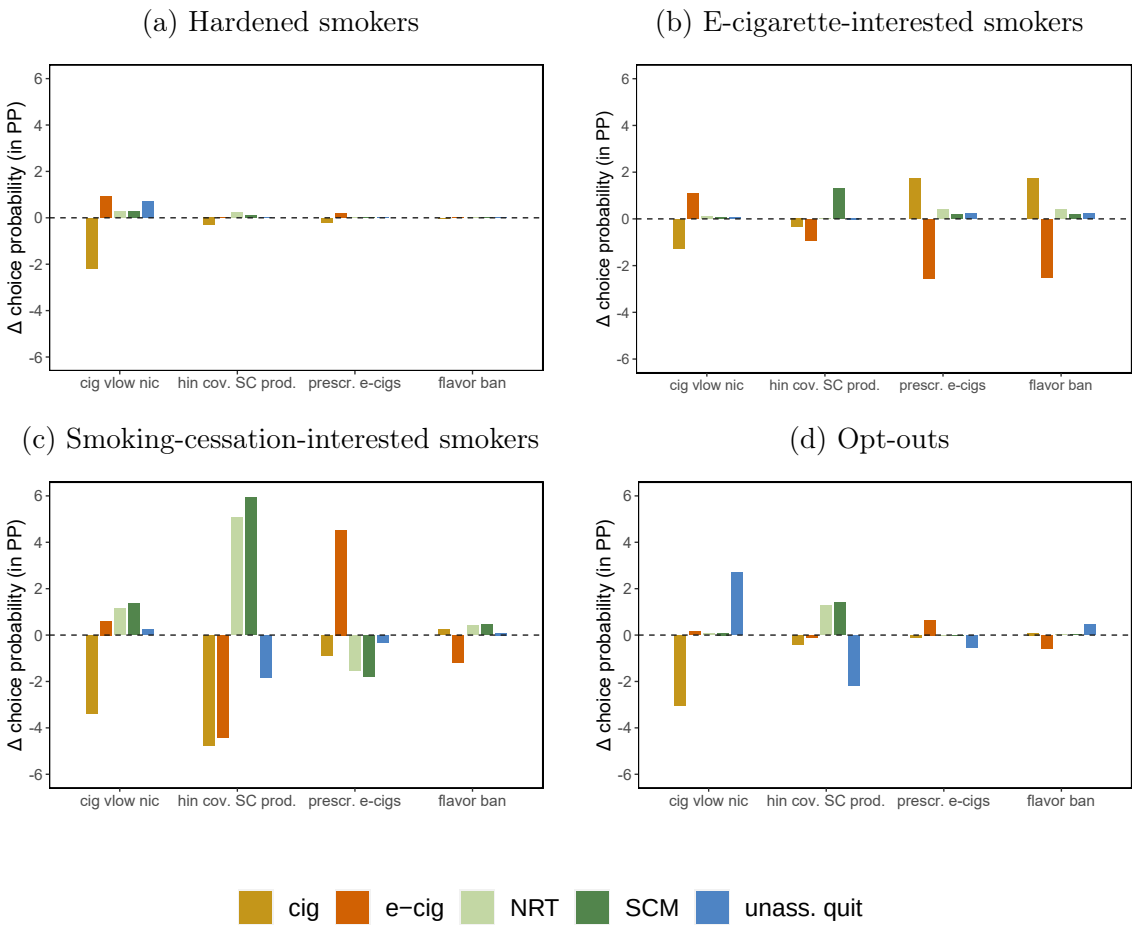


Note: The figure shows the predicted changes in choice probabilities (in percentage points) for the five tobacco and smoking cessation products/behaviors considered in response to four tobacco policies (described in Table 3.C.2). Panel (a) shows the predictions based on the parameter estimates from the latent class logit model accounting for preference heterogeneity, while the predictions in Panel (b) are based on parameter estimates from the conditional logit model (imposing preference heterogeneity). Class-specific predictions of choice probabilities in the latent class model are aggregated at the population level using estimated class shares.

Whereas Figure 3.2a, although accounting for preference heterogeneity, shows the responses to potential policies aggregated at the population level, exploring the responses separately by smoker type may provide additional insights into smokers' choice behavior. Figure 3.3 reveals that reducing nicotine in tobacco cigarettes appears to be an effective policy for all

smoker types. Moreover, Figure 3.3a suggests that the aggregated latent class results in 3.2a are mainly driven by hardened smokers, the largest and most insensitive group of smokers. However, 17.9% of smokers – smoking-cessation-interested smokers – react strongly to the policies examined, as depicted in Figure 3.3c. Smoking-cessation-interested smokers strongly respond to insurance coverage of smoking cessation products. They increase their demand for NRTs and SCMs when covered by insurance. In return, this policy is predicted to reduce cigarette uptake by 4.8 percentage points (or 29.3%). Additionally, this group positively reacts to the prescription requirement for e-cigarettes. The introduction of prescription e-cigarettes is predicted to increase e-cigarette choice by 4.5 percentage points (or 30.2%) and to reduce cigarette choice by 0.9 percentage points (or 5.3%). In contrast, for e-cigarette-interested

Figure 3.3: Class-specific policy scenario simulations



Note: The figure shows the predicted changes in choice probabilities (in percentage points) for the five tobacco and smoking cessation products/behaviors considered, separately for each smoker type, in response to four tobacco policies (described in Table 3.C.2). Predictions are based on the class-specific taste parameter estimates from the LCL model. Panel (a) presents the responses for hardened smokers (51.8% of smokers), Panel (b) for e-cigarette-interested smokers (20.3%), Panel (c) for smoking-cessation-interested smokers (17.9%), and Panel (d) for opt-outs (9.93%). For detailed prediction results, we refer to Appendix Table 3.C.4.

smokers, the prescription requirement for e-cigarettes reduces the probability of choosing e-cigarettes by 2.6 percentage points (or 3.9%). As an unintended consequence of this policy, e-cigarette-interested smokers are predicted to substitute prescription e-cigarettes with more harmful, conventional cigarettes (+1.7 percentage points; or +7.2%).

E-cigarette flavors appear to be less important for smokers' choices. Only the e-cigarette-interested smokers are expected to reduce their demand for e-cigarettes in response to a flavor ban (-2.5 percentage; or -3.9%) and substitute unflavored e-cigarettes for tobacco cigarettes (+1.7 percentage points; or +7.2%). The simulation of more complex, multi-action policy scenarios is included in the Appendix (see Section 3.B.1). In summary, multiple-action scenarios support our finding that hardened smokers and opt-outs do not respond to policies other than reducing nicotine content in cigarettes. Moreover, results from these analyses emphasize that simultaneously introducing several policies that reduce the attractiveness of commercial e-cigarettes (i.e., prescription requirement and flavor ban), can lead to a considerable increase in cigarette uptake among e-cigarette-interested smokers. Furthermore, for smoking-cessation-interested smokers, reducing nicotine in cigarettes and at the same time introducing insurance coverage of NRTs and SCMs appears to be the most effective approach.

Finally, we return to our hypotheses outlined in the conceptual framework in Section 3.2.2. Our data partially supports the first prediction that smokers reduce their quantity demanded if the product's financial price increases (either by an increase in product prices or reduced insurance coverage). However, there is considerable heterogeneity in the price sensitivity across different types of smokers. Whereas smoking-cessation-interested smokers react strongly to price changes of all products considered, the other smoker types demonstrate much lower price sensitivity, with hardly any reaction to price changes being predicted for hardened smokers. Hence, our first prediction holds mainly for the subgroup of smoking-cessation-interested smokers, and partially for e-cigarette-interested smokers and opt-outs. The second prediction, regarding hassle costs associated with prescription e-cigarettes, is supported by two out of four classes in our analyses. For e-cigarette-interested smokers, hassle costs may discourage the use of e-cigarettes, while the positive signalling in terms of product safety and social desirability appears to outweigh the additional costs from requiring a prescription among smoking-cessation-interested smokers. Flavor bans seem to affect only around one fifth of the smoker population (e-cigarette-interested smokers). Hence, the third prediction is only supported by a specific subgroup of smokers, presumably dual users, that consume both e-cigarettes and tobacco cigarettes. Based on our findings, the fourth prediction applies to all smoker types. Low nicotine levels in cigarettes appear to reduce experienced benefits from smoking and thus reduce demand for tobacco cigarettes.

3.6 Discussion and conclusion

We conduct a labeled discrete choice experiment (DCE) to explore the preferences of U.S. adult smokers for various tobacco and smoking cessation products, and to predict changes in product choices in response to various policy scenarios applied to the tobacco market. Specifically, we simulate the potential responses to changes in nicotine levels, prices, flavors, and requiring a prescription for the product. Using a latent class logit model, we identify four distinct classes of U.S. smokers. The majority of smokers (51.8%) in our sample, labeled as *hardened smokers*, have a strong preference for cigarettes, regardless of product characteristics. These smokers display high levels of addiction and appear not willing (or not able) to quit. For hardened smokers, apart from the nicotine reduction in tobacco cigarettes, the policies considered appear ineffective in terms of reducing smoking. Another smoker type labeled as *opt-outs*, representing 9.93% of the overall sample, predominately selects unassisted quitting and does not display strong preferences for any of the products considered. The remaining two smoker types most frequently select tobacco cigarettes and e-cigarettes (20.3% of smokers), and smoking cessation products (17.9% of smokers), respectively. These two smoker types, labeled as *e-cigarette-interested smokers* and *smoking-cessation-interested smokers*, are somewhat sensitive to tobacco policies. The distinct groups of smokers are observably different in terms of demographics such as age, education, income, risk perceptions, and current smoking and vaping habits.

Regarding the demand for e-cigarettes, our analyses support previous studies' findings and the current political view that smokers consume e-cigarettes for different motives (see e.g., Eaton et al., 2018; Owusu et al., 2019; Patel et al., 2016). In our sample, 20.3% − e-cigarette-interested smokers − appear to be dual users who prefer various e-cigarette flavors and dislike prescription e-cigarettes. Most of them (85%) report using e-cigarettes at least occasionally and 34% report daily vaping. Hence, these smokers seem to value e-cigarettes as a commercial product rather than a smoking cessation tool. In contrast, 17.9% − smoking-cessation-interested smokers − likely value e-cigarettes as a medical product. This smoker type prefers prescription e-cigarettes, hardly uses commercial e-cigarettes, and demonstrates a high willingness to quit smoking. Thus, prescription e-cigarettes might discourage one group of smokers from using tobacco cigarettes, while leading to the increase in smoking for another group.

Our findings suggest that due to the heterogeneity in smokers' preferences and motives, designing one-fits-all tobacco policies convincing all smokers to quit, to reduce their tobacco consumption, or to switch to less harmful options is challenging at best and infeasible at worst. Tailoring policies to specific subgroups of smokers might help to solve the trade-off of promoting health-improving behavior for some smokers while discouraging health-harming behavior among others. However, implementing tailored policies is not always possible because policymakers may not have the possibility to clearly identify and apply different regulations to

different subgroups of the population. A further challenge is that these population subgroups are often defined not just by demographics but also the complexity of internal factors (e.g., motivations or reasons to use the product, risk perceptions, attitudes and beliefs). Nevertheless, as proposed in Duarte and Choi (2021), the information on heterogeneous preferences and the psychographic profiles[18] of smoker types might be valuable for the implementation of tailored communication strategies along with policy reforms rather than tailoring policies itself.

This study expands existing findings on smokers' choice behavior and the effective design of smoking cessation policies in several ways. First, we consider a wide set of tobacco and smoking cessation products, reflecting the current market situation well. Second, in addition to studying preference heterogeneity, we also explore possible drivers thereof by analyzing smokers' profiles using a rich set of background characteristics. Third, we predict responses to newly proposed, but as of the time of writing not implemented, tobacco polices in the U.S. Finally, the knowledge on the population shares of the different smoker types and their distinct reactions to policies can help to improve simulation models used for prediction (e.g., SimSmoke Tobacco Control Policy Simulation Model)[19] (for a review see e.g., Feirman et al., 2017).

While the study provides valuable insights, there are some limitations that are important to consider when interpreting the findings. In particular, we face methodological shortcomings related to the DCE application which is of hypothetical nature. This might cause concerns about external validity and whether the real-world decisions coincide with the hypothetical choices. We rely on a selected subset of product attributes and levels, which potentially may not describe the full picture of the product characteristics, and thus may simplify the decision of the respondents. Moreover, we rely on an online panel sample, more likely to reach healthier, younger, more educated, and technologically more advanced individuals. Furthermore, the estimation models used assume proportional substitution between tobacco and smoking cessation products (for details, see e.g., Train, 2009). Finally, we focus on preferences of smokers. The analysis of the responses of non-smokers, especially adolescents and young adults, to the policies discussed is left for future research.

Overall, our findings suggest that policymakers should always consider the diversity of preferences for tobacco products and motives for product use within the population of U.S. adult smokers. Given that a non-trivial share of U.S. residents continue to smoke, despite well-known health harms and dynamic changes in the U.S. tobacco market, ignoring the heterogeneity of factors motivating smokers to choose potentially less harmful products may lead to welfare losses and possibly worsens public health.

[18]Chandler and Munday (2011) define psychographics as a segmentation of a population according to their values, attitudes, opinions, interests, personalities, and lifestyles rather than demographic factors.

[19]The SimSmoke model is a macro model that is utilized to simulate the effect of various tobacco control policies on smoking rates and on smoking-related deaths for the U.S., both at the level of the nation and state. The model, which has been utilized in over 50 academic studies, is based on a discrete Markov model.

3.A Supplementary material: survey design and estimation method

3.A.1 Experimental design and assessing the design quality

The selected attributes and their levels, depicted in Table 3.2, define three distinct product profiles for cigarettes, 18 profiles for e-cigarettes, three profiles for NRTs, and six profiles for SCMs.[20] Therefore, when constructing the choice tasks presented to the respondents, we must choose a subset of all 972 possible combinations of product profiles.[21] To facilitate this construction of choice tasks, we use an efficient design which maximizes the effective information received out of each choice task (see Ryan et al., 2012, for details on experimental design selection and DCE design in general). Specifically, we use the modified Fedorov algorithm of the Ngene software (Ngene, 2018) to generate an experimental design including 32 choice tasks. These 32 choice tasks are split into four versions, each containing eight analysis choice tasks. Each respondent is randomly assigned to one version and has to complete eight main choice tasks, one practice task, and one test-retest task.[22] The test-retest task is used to measure response consistency by comparing the respondent's choices for the test task and retest task in the survey, two tasks presenting exactly the same choice situation. This check is frequently used to assess response quality (Pearce et al., 2021). We implement a 'forced response' approach to ensure that all choice tasks in the DCE are answered, without skipping through the survey. We use attention filters in the survey (e.g., 'select option two') to assess whether the respondents pay attention to the tasks. We only keep data from respondents that selected the correct option in this attention filter. Further indicators of response quality are considered, such as median time for completion of the survey and self-reported accuracy of answers.

The survey was pilot tested online with 155 respondents, whereby apart from performing the technical check, the data was used to obtain the priors to improve the efficiency of the experimental design. Following standard practice to generate priors, a testing sample with 155 respondents is considered sufficient. Moreover, the pilot test was used to verify whether the layout of the questionnaire is clear to the respondents.

[20] The number of distinct product profiles is calculated based on the number of attributes and their levels. For cigarettes: 1 attribute at 3 levels, 3 attributes at 1 level; For e-cigarettes: 1 attribute at 6 levels, 2 attributes at 3 levels, 1 attribute at 2 levels; For NRTs: 1 attribute at 3 levels, 3 attributes at 1 level; For SCMs: 1 attribute at 3 levels, 1 attribute at 2 levels, 2 attributes at 1 level.

[21] $\prod_{j=1}^{5} \#profiles_j = 3 \times 18 \times 3 \times 6 \times 1 = 972$

[22] Note that the order in which the eight choice tasks are presented to the respondents is also randomized and therefore differs across respondents.

3.A.2 Definition of attributes and attribute levels

As described in Section 3.3.1, our DCE includes four attributes: out-of-pocket price, nicotine content, prescription requirement, and flavor. For the determination of prices, we rely on previously published studies, adjusting for the current price levels and latest retail consumer data. We anchor the prices of all tobacco and smoking cessation products to a comparable unit, which is equal to smoking a pack of 20 cigarettes (Cheng et al., 2021; Liber et al., 2017). The cigarette price is fixed and based on the 2019 Tax Burden on Tobacco report (Centers for Disease Control and Prevention, 2023c). The price levels for refillable vape pen and the starting kit are based on earlier studies (Buckell et al., 2020; Cheng et al., 2021), prices of NRT on 2020 Neilsen data, and the prices of Chantix SCM on recent literature (Maclean et al., 2019).
The nicotine levels of NRT gums and refillable vape pens are retrieved from earlier studies (Wadgave and L., 2016). The nicotine levels of cigarettes represent the current nicotine content in regular cigarettes (12 mg), light (6mg, -50%), and very light cigarettes with minimal or non-addictive nicotine levels (0.6mg, -95%). Reducing nicotine content to very low, and potentially non-addictive levels is currently discussed as a potential smoking cessation policy in the U.S. (Food and Drug Administration, 2018; Thompson, Don, 2023).
The selection of the flavor categories for e-cigarettes [None, Various, Menthol only] is based on market availability; and on findings that the main reason for young adults to use e-cigarettes are sweet flavors, while adults (smokers), who might use e-cigarettes as a harm reduction tool, prefer unflavored e-cigarettes (i.e., tobacco flavor) (Soneji et al., 2019).

3.A.3 Likelihood function of the latent class model

In the latent class logit model, the probability that an individual i, belonging to class c, chooses product j in choice task t corresponds to the following logit choice probability (Pacifico and Yoo, 2013; Train, 2009):

$$P_{it}(j \mid c) = \frac{exp(\boldsymbol{\beta_c x_{ijt}})}{\sum_{k=1}^{J} exp(\boldsymbol{\beta_c x_{ikt}})} \tag{3.A.1}$$

where $\boldsymbol{\beta_c}$ corresponds to the class-specific taste parameters and $\boldsymbol{x_{ijt}}$ to the vector of product attribute levels of product j as presented to respondent i in choice task t.
Using these conditional choice probabilities, the class-specific probability of observing a given sequence of choices for some individual i over all choice tasks t can be specified as follows:

$$P_i(\boldsymbol{\beta}_C) = \prod_{t=1}^{T} \prod_{j=1}^{J} \left\{ \frac{exp(\boldsymbol{\beta_c x_{ijt}})}{\sum_{k=1}^{J} exp(\boldsymbol{\beta_c x_{ikt}})} \right\}^{y_{ijt}} \tag{3.A.2}$$

where y_{ijt} equals one for the chosen alternative in choice task t. Note that this probability varies

with class membership c in the presence of preference heterogeneity, because $\boldsymbol{\beta_c}$ differs across classes. Given that class membership is ex-ante unknown and determined within the model, latent class uses a weighted average over the C class-specific conditional probabilities to obtain unconditional probabilities. The weights correspond to individual-specific class membership probabilities π_{ci}.

$$P_i = \sum_{c=1}^{C} \pi_{ci}(\boldsymbol{\theta}) P_i(\boldsymbol{\beta}_C), \quad \text{where } \pi_{ci}(\boldsymbol{\theta}) = \frac{exp(\boldsymbol{\theta}_c \boldsymbol{z}_i)}{1 + \sum_{l=1}^{C-1} exp(\boldsymbol{\theta}_l \boldsymbol{z}_i)} \tag{3.A.3}$$

The class membership probabilities are determined based on the smokers' choice patterns in the DCE and can be modeled as a function of individual characteristics, where $\boldsymbol{z_i}$ is a vector of individual specific variables. In our setting, we include age, family income, education, health insurance, smoking and vaping habits, as well as smoking and vaping risk perceptions.
Finally, the sample log-likelihood function of the latent class logit model then consists of the sum of the unconditional probabilities over all individuals in the sample, as depicted in Equation (3.A.4). Taste and class membership parameters are thus estimated as to maximize this log-likelihood function.

$$lnL(\boldsymbol{\beta}, \boldsymbol{\theta}) = \sum_{i=1}^{N} lnP_i \tag{3.A.4}$$

For more detailed information on the conditional logit and the latent class logit model, we refer to Train (2009), Bhat (1997), and Pacifico and Yoo (2013).

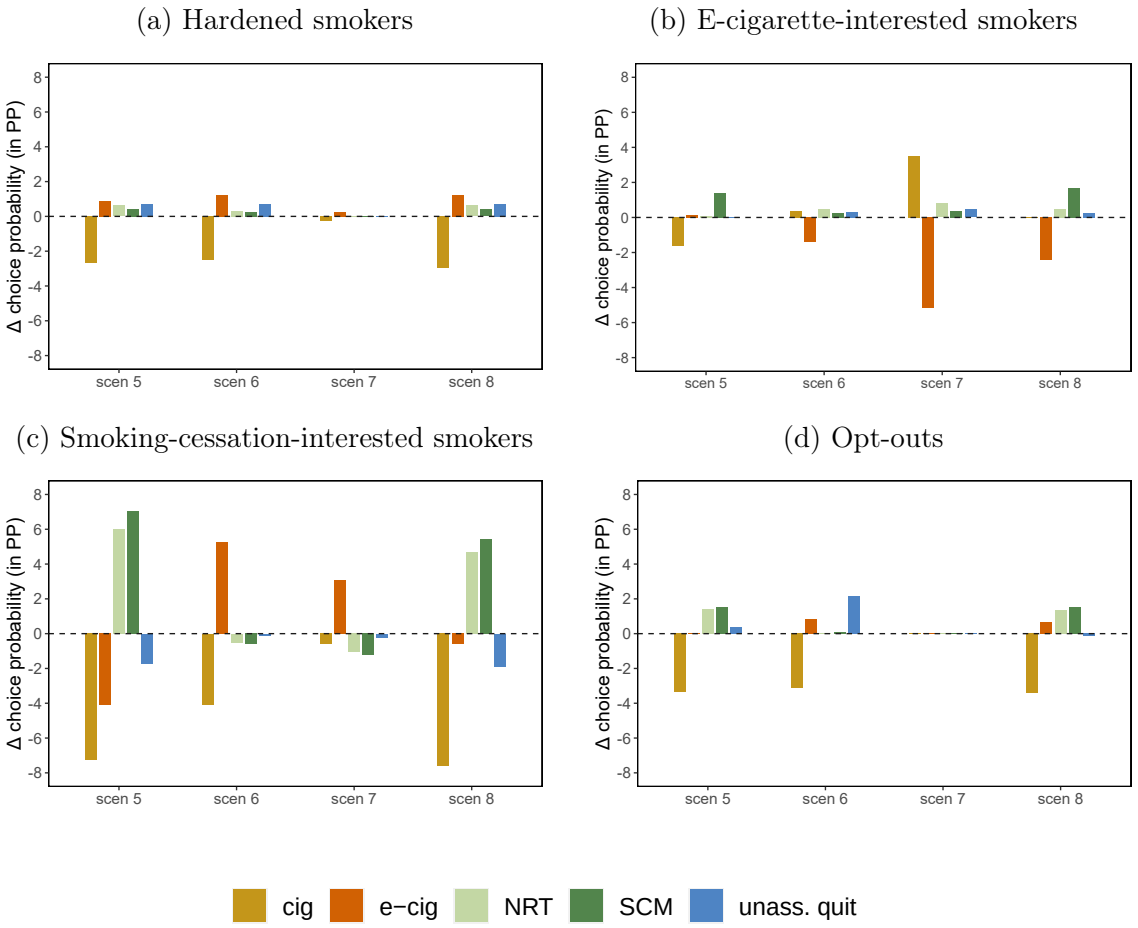
3.B Supplementary results and analyses

3.B.1 Simulation of multiple-actions policies

Figure 3.B.1 depicts the responses of the four smoker types to the multiple-actions policies described in Table 3.C.2. The predictions suggest that for hardened smokers and opt-outs only decreasing nicotine content in cigarettes (in scenario 5, 6 and 8) significantly affects choice probabilities. These findings are consistent with the conclusion from our analysis of single-action policies. For e-cigarette-interested smokers, decreasing nicotine content in cigarettes while simultaneously increasing the attractiveness of smoking cessation products (by insurance coverage) in scenario 5 leads to a reduction in cigarette uptake. Our model predicts that, under these circumstances, e-cigarette-interested smokers are more likely to substitute cigarettes with SCMs than to switch to e-cigarettes.
Moreover, Figure 3.B.1 Panel b reveals that restricting access to commercial e-cigarettes (i.e.,

requiring a prescription) and at the same time banning flavored e-cigarettes, in scenario 7, strongly reduces the attractiveness of e-cigarettes for e-cigarette-interested smokers. As an unintended consequence, e-cigarette-interested smokers likely switch back to cigarettes. Cigarette uptake is predicted to increase by 3.5 percentage points (or 14.6%). For this smoker type, once we introduce policies that reduce the attractiveness of or the access to commercial e-cigarettes, the benefit of any considered smoking-reducing policy is fully offset.
For the smoking-cessation-interested smokers, the predictions for the multiple-actions policies indicate that especially reducing the attractiveness of cigarettes while simultaneously increasing

Figure 3.B.1: Class-specific policy scenario simulations: multiple-actions policies



Note: The figure shows the predicted changes in choice probabilities (in percentage points) for the five tobacco and smoking cessation products/behaviors considered, separately for each smoker type, in response to four multiple-actions tobacco policies. For detailed prediction results, we refer to Appendix Table 3.C.4. Scenario 5: Very low nicotine cigarettes + health insurance coverage of NRTs and SCMs. Scenario 6: Very low nicotine cigarettes + prescription e-cigarettes. Scenario 7: prescription e-cigarettes + ban of flavored e-cigarettes. Scenario 8: Very low nicotine cigarettes + health insurance coverage of NRTs/SCMs + prescription e-cigarettes. These scenarios are described in Table 3.C.2 in the Appendix (multiple-actions scenarios 5−8). Panel (a) presents the responses for hardened smokers (51.8% of smokers), Panel (b) for e-cigarette-interested smokers (20.3%), Panel (c) for smoking-cessation-interested smokers (17.9%), and Panel (d) for opt-outs (9.93%).

the financial attractiveness of smoking cessation products (scenario 5) appears beneficial. In this scenario, cigarette uptake is predicted to decrease by 7.3 percentage points (or 44.6%). Furthermore, the results suggest that the additional benefit of introducing prescription requirement for e-cigarettes is rather small.

3.B.2 Attribute importance for smokers' product choices

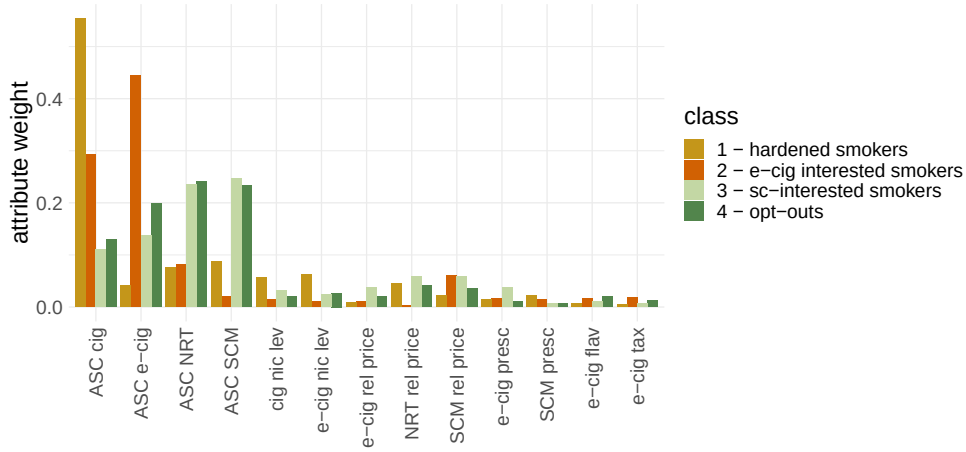
Figure 3.B.2 displays the relative importance of an attribute in the smokers' choice of tobacco and smoking cessation products. The attribute importance weights are calculated using the range method (see e.g., Nicolet et al., 2020). In this approach, preference weights of the product constants and the four product attributes are set in relation to each other. Specifically, the range method defines the importance weight of an attribute as follows:

$$W_{attribute(k)} = \frac{max\hat{\boldsymbol{\beta}}_{\boldsymbol{k}} - min\hat{\boldsymbol{\beta}}_{\boldsymbol{k}}}{\sum_l (max\hat{\boldsymbol{\beta}}_{\boldsymbol{l}} - min\hat{\boldsymbol{\beta}}_{\boldsymbol{l}})},$$

where the numerator represents the difference in preference weights between the best case and the worst case attribute level (e.g., the highest price and the lowest price). This difference is then normalized by the sum of such differences across all the attributes.

Figure 3.B.2 confirms our findings that smokers have a strong attachment to a specific product type. Whereas hardened smokers clearly prefer cigarettes, e-cigarette-interested smokers value both cigarettes and e-cigarettes. Moreover, smoking-cessation-interested smokers prefer NRTs and SCMs. In comparison, product attributes such as nicotine, prices, prescription, and flavors seem to be much less important in the choice of tobacco and smoking cessation products.

Figure 3.B.2: Attribute importance



Note: This figure displays the relative importance of an attribute in the smokers' choice of tobacco and smoking cessation products. Attribute importance weights are calculated using the range method.

3.B.3 Robustness checks

According to Table 3.5, consistency rates are relatively low for the classes of e-cigarette-interested smokers (58.7%) and smoking-cessation-interested smokers (58.9%). Only using observations from respondents with consistent answers yields very similar classes and preference patterns (see Table 3.B.1) compared to our main results in Table 3.3. Although consistent respondents are found to be slightly more price sensitive, the overall conclusions remain unchanged.

Table 3.B.1: Robustness: LCL taste parameter estimates for consistent respondents

	Class 1	**Class 2**	**Class 3**	**Class 4**
Relative class size	*61.1%*	*14.7%*	*13.7%*	*10.5%*
ASC: Cigs	4.432***	2.396***	1.176***	-2.07***
	(0.168)	(0.307)	(0.235)	(0.265)
ASC: SCM (Chantix)	-0.335	0.603	2.578***	-2.914***
	(0.31)	(0.384)	(0.231)	(0.504)
ASC: E-cigs	0.54	4.579***	1.473***	-2.197***
	(0.368)	(0.349)	(0.365)	(0.584)
ASC: NRT (gum)	-0.455.	0.923**	2.407***	-2.948***
	(0.275)	(0.322)	(0.252)	(0.339)
ASC: Unassisted quitting	ref. group			
Need for prescription to obtain SCM	-0.178	0.085	0.013	-0.086
	(0.239)	(0.303)	(0.065)	(0.347)
Need for prescription to obtain e-cigs	0.244	-0.387***	0.204	-0.22
	(0.152)	(0.092)	(0.161)	(0.258)
Nicotine level cigs: Regular (12mg)	base level			
Nicotine level cigs: Low (6mg)	0.081	0.116	-0.219	0.088
	(0.134)	(0.14)	(0.185)	(0.197)
Nicotine level cigs: Very low (0.6mg)	-0.301.	0.119	-0.624*	-0.42
	(0.155)	(0.182)	(0.245)	(0.288)
Nicotine level e-cigs: Regular (3mg)	base level			
Nicotine level e-cigs: Low (1.5mg)	-0.516*	-0.161	-0.259	0.37
	(0.216)	(0.107)	(0.159)	(0.229)
Nicotine level e-cigs: Very low (0.15mg)	-0.127	-0.176	-0.179	0.303
	(0.182)	(0.11)	(0.19)	(0.296)
Relative price for SCM	-0.696*	-0.764.	-0.46***	-0.949.
	(0.353)	(0.392)	(0.099)	(0.506)
Relative price for NRT gum	-0.968.	-0.516	-0.683***	-2.067*
	(0.534)	(0.39)	(0.139)	(0.832)
Relative price for e-cigs	-0.479	-0.49*	-0.87*	-0.993
	(0.41)	(0.246)	(0.433)	(0.612)
Price for e-cigs includes tax	0.059	-0.039	0.033	0.058
	(0.155)	(0.086)	(0.154)	(0.221)
E-cigarettes with various flavors	base level			
E-cigarettes with menthol flavor	-0.043	-0.148	-0.228	-0.388
	(0.191)	(0.11)	(0.182)	(0.278)
E-cigarettes with no flavor	0.246	-0.173.	-0.102	-0.296
	(0.167)	(0.095)	(0.146)	(0.315)

Note: This table presents the class-specific taste parameter estimates from the LCL model for the subsample of respondents with consistent answers in the test-retest-task. The first row reveals the share of the sample used to estimate the taste parameters (i.e., the relative class size). To estimate the parameters with maximum likelihood, we used the apollo package in R. Standard errors are heteroskedasticity robust and clustered at the individual level to account for the panel structure of the data. Significance codes: . $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

3.C Additional tables

Table 3.C.1: Description of the collected background characteristics

Variable	Description / Survey question
Age	Age at the time of completing the survey
Female	= 1 if female, = 0 if male
Low education (below high school)	Highest completed level of education is below high school
Employed	Individuals are designated as *employed* if they are either employed for wages or self-employed
Unemployed	Unemployed at the time of completing the survey
Family income	Total family income before taxes; includes income from all family members living at home and all sources of income.
Has health insurance	Indicates whether the respondent has health insurance at the time of answering the survey (yes = 1, no = 0).
Daily smoker	Indicates whether the respondent smokes cigarettes every day (yes = 1, no = 0).
Time to first cigarette after wake up	How soon after waking do you usually smoke your first cigarette? (Within 5 minutes; 6-30 minutes; 31-60 minutes; more than 60 minutes min)
Past quit attempt	Have you tried to quit smoking cigarettes at least once in the last year? (yes = 1, no =0)
Ever tried e-cigarettes	Have you ever used an e-cigarette or other electronic vaping product, even just one time, in your entire life? (yes = 1, no = 0)
Daily vaper	Indicates whether the respondent uses e-cigarettes every day (yes = 1, no = 0).
No e-cigarette use	Indicates whether the respondent uses e-cigarettes not at all (yes = 1, no = 0).
Subjective smoking risk perception	Respondent's estimate of how many out of 100 cigarette smoker will die from lung cancer, heart disease, throat cancer, or any other illness because they smoke tobacco cigarettes.
Subjective vaping risk perception	Respondent's estimate of how many out of 100 e-cigarette users will die from lung cancer, heart disease, throat cancer, or any other illness because they vape.
Vaping equally / more risky	Respondents were asked whether they agree with the statement that e-cigarettes are equally or more harmful to health than cigarettes (yes = 1, no = 0).
Completion time	Measures the time (in minutes) it takes a respondent to complete the survey.
Consistent answer	= 1, if a respondent consistently chooses the same option in the test and the retest task, two tasks showing exactly the same choice situation.

Note: This table describes the variables on current smoking and vaping habits, background characteristics, and subjective risk perceptions used in the analysis. Specifically, these variables are used in the descriptive statistics and the estimation of class membership probabilities.

Table 3.C.2: Description of policy scenarios

	Policy scenario	Description
		Single-action policies
1	Nicotine level in cigarettes reduced by 95% (very low)	Potentially decreasing attractiveness of cigarettes by reducing their nicotine content to minimal or medically non-addictive level.
2	Health insurance covers 100% of costs for NRTs and SCMs	Potentially increasing attractiveness of SCMs and NRTs (clinically approved less harmful options for quitting) by reducing out-of-pocket costs.
3	Medical prescription is required to obtain e-cigarettes	Potentially decreasing attractiveness of e-cigarettes for smokers prefering commercial e-cigarettes while increasing attractiveness for those wishing to switch to less harmful options or to quit.
4	Ban of flavored e-cigarettes	Potentially reducing attractiveness of e-cigarettes for dual users, while not affecting smokers that use e-cigarettes as smoking cessation tool (as they usually prefer non-flavored e-cigarettes).
		Multiple-actions policy
5	Scenario 1 + Scenario 2	Intended at decreasing attractiveness of cigarettes while increasing attractiveness of SCMs and NRTs.
6	Scenario 1 + Scenario 3	Intended at decreasing attractiveness of cigarettes while increasing attractiveness of e-cigarettes as a tool for smoking cessation.
7	Scenario 3 + Scenario 4	Increasing attractiveness of e-cigarettes as a tool for smoking cessation while decreasing attractiveness of e-cigarettes for commercial use (dual users and non-smokers) by restricting access and by banning flavors.
8	Scenario 1 + Scenario 2 + Scenario 3	Intended at decreasing attractiveness of cigarettes, raising financial attractiveness of lower-harm medical products (NRT, SCM), and positioning e-cigarettes as a medicinal product received only by prescription.

Note: The policy scenarios are chosen based on possible tobacco control policies currently discussed in the U.S. For the policy scenario simulation, only the described changes of attribute levels in each scenario are performed, all other attribute levels remain at baseline (status quo). **Baseline:** Current daily costs: USD 9 for cigarettes, USD 4 for vape pens, USD 6 for NRTs and USD 9 for SCM. Prescription requirement for SCM, but not for e-cigarettes. Regular nicotine levels for cigarettes and e-cigarettes. No e-cigarette tax. Availability of various e-cigarette flavors.

Table 3.C.3: Latent class model: estimated class-membership parameters

	Class 1	**Class 2**	**Class 3**	**Class 4**
Reference group: Class 1 (hardened smokers)				
Behavior: Daily smoker	-	-1.176***	-0.956***	-1.884***
	(-)	(0.154)	(0.159)	(0.167)
Behavior: Daily e-cigarette user	-	1.657***	0.304	-0.198
	(-)	(0.146)	(0.186)	(0.295)
Behavior: Past cig. quit attempt	-	0.761***	1.086***	0.903***
	(-)	(0.108)	(0.105)	(0.131)
Risk perc smoking: Medium [p25,p75]	base level			
Risk perc smoking: High (> p75)	-	-0.191	-0.082	0.277
	(-)	(0.143)	(0.134)	(0.182)
Risk perc smoking: Low (< p25)	-	-0.338*	-0.476**	0.18
	(-)	(0.141)	(0.142)	(0.183)
Risk perc smoking: Missing	-	-0.524**	-0.578***	0.433*
	(-)	(0.155)	(0.15)	(0.167)
Risk perc: Vaping equally / more risky	-	-0.798***	-0.106	0.067
	(-)	(0.107)	(0.106)	(0.134)
Socio demogr.: Age	-	-0.033***	-0.005	0.021**
	(-)	(0.005)	(0.005)	(0.006)
Socio demogr.: Edu - lower than highschool	-	-0.56*	-0.62*	0.529*
	(-)	(0.284)	(0.276)	(0.215)
Socio demogr.: Employed	-	0.369**	0.205.	-0.045
	(-)	(0.12)	(0.114)	(0.146)
Socio demogr.: Family income (ordered cats)	-	0.054*	0.062**	-0.082**
	(-)	(0.022)	(0.022)	(0.026)
Socio demogr.: Has health insurance	-	0.376*	0.854***	-0.131
	(-)	(0.168)	(0.196)	(0.174)

Note: The table presents the coefficient estimates, θ_c, from the fractional multinomial logit model in Equation (3.A.3). The coefficient estimates reveal how class membership probabilities are related to smokers' characteristics, smoking and vaping habits, and risk perceptions. Class 1 (hardened smokers) is used as the reference group. The estimated coefficients support the descriptive differences in respondents' characteristics between classes, depicted in Table 3.5. Robust standard errors clustered at the individual level are reported in parentheses. Significance codes: . p < 0.1; * p< 0.05; ** p< 0.01; *** p< 0.001.

Table 3.C.4: Policy scenario simulation

		Class 1 (Hardened smokers) Δ PP (Δ %)					Class 2 (E-cig-interested smokers) Δ PP (Δ %)				
		Cig	E-Cig	NRT	SCM	quit unass.	Cig	E-Cig	NRT	SCM	quit unass.
1	Cig vlow nic	-2.19 (-2.30)	0.92 (49.1)	0.29 (49.1)	0.27 (49.1)	0.72 (49.1)	-1.28 (-5.35)	1.10 (1.69)	0.09 (1.69)	0.04 (1.69)	0.05 (1.69)
2	Hin cov. SC prod.	-0.31 (-0.33)	-0.01 (-0.33)	0.23 (38.9)	0.09 (17.3)	-0.01 (-0.33)	-0.34 (-1.43)	-0.93 (-1.43)	-0.00 (-0.02)	1.31 (50.4)	-0.04 (-1.43)
3	Prescr. e-cigs	-0.21 (-0.22)	0.22 (11.5)	-0.00 (-0.22)	-0.00 (-0.22)	-0.00 (-0.22)	1.74 (7.24)	-2.55 (-3.93)	0.40 (7.24)	0.19 (7.24)	0.23 (7.24)
4	Flavor ban	-0.02 (-0.02)	0.02 (1.07)	0.00 (-0.02)	0.00 (-0.02)	0.00 (-0.02)	1.72 (7.17)	-2.52 (-3.89)	0.39 (7.17)	0.19 (7.17)	0.22 (7.17)
5	Scenario 5	-2.65 (-2.77)	0.9 (48.4)	0.63 (107)	0.4 (74.6)	0.71 (48.4)	-1.61 (-6.72)	0.14 (0.21)	0.09 (1.65)	1.38 (52.9)	0.01 (0.21)
6	Scenario 6	-2.50 (-2.62)	1.23 (66.1)	0.29 (48.6)	0.26 (48.6)	0.71 (48.6)	0.39 (1.63)	-1.42 (-2.19)	0.5 (9.19)	0.24 (9.19)	0.29 (9.19)
7	Scenario 7	-0.23 (-0.24)	0.24 (12.7)	-0.00 (-0.24)	-0.00 (-0.24)	-0.00 (-0.24)	3.51 (14.6)	-5.14 (-7.93)	0.80 (14.6)	0.38 (14.6)	0.46 (14.6)
8	Scenario 8	-2.95 (-3.09)	1.22 (65.3)	0.63 (106)	0.40 (74.1)	0.70 (47.9)	0.01 (0.05)	-2.41 (-3.71)	0.49 (9.03)	1.67 (64.0)	0.23 (7.49)

		Class 3 (Smoking-cessation-interested smokers) Δ PP (Δ %)					Class 4 (Opt-outs) Δ PP (Δ %)				
		Cig	E-Cig	NRT	SCM	quit unass.	Cig	E-Cig	NRT	SCM	quit unass.
1	Cig vlow nic	-3.37 (-20.7)	0.60 (4.02)	1.16 (4.02)	1.35 (4.02)	0.25 (4.02)	-3.03 (-21.1)	0.16 (3.53)	0.07 (3.53)	0.09 (3.53)	2.71 (3.53)
2	Hin cov. SC prod.	-4.77 (-29.3)	-4.41 (-29.3)	5.08 (17.6)	5.93 (17.6)	-1.84 (-29.3)	-0.40 (-2.81)	-0.12 (-2.81)	1.29 (66.4)	1.40 (56.0)	-2.16 (-2.81)
3	Prescr. e-cigs	-0.87 (-5.33)	4.53 (30.2)	-1.54 (-5.33)	-1.79 (-5.33)	-0.33 (-5.33)	-0.10 (-0.68)	0.65 (14.7)	-0.01 (-0.68)	-0.02 (-0.68)	-0.52 (-0.68)
4	Flavor ban	0.23 (1.39)	-1.18 (-7.86)	0.40 (1.39)	0.47 (1.39)	0.09 (1.39)	0.09 (0.61)	-0.58 (-13.2)	0.01 (0.61)	0.02 (0.61)	0.47 (0.61)
5	Scenario 5	-7.25 (-44.6)	-4.11 (-27.3)	6.03 (20.9)	7.05 (20.9)	-1.71 (-27.3)	-3.35 (-23.36)	0.02 (0.52)	1.4 (72.1)	1.53 (61.3)	0.4 (0.52)
6	Scenario 6	-4.08 (-25.1)	5.27 (35.1)	-0.50 (-1.74)	-0.58 (-1.74)	-0.11 (-1.74)	-3.1 (-21.6)	0.83 (18.8)	0.05 (2.80)	0.07 (2.80)	2.15 (2.80)
7	Scenario 7	-0.59 (-3.61)	3.07 (20.4)	-1.04 (-3.61)	-1.21 (-3.61)	-0.23 (-3.61)	0.00 (0.01)	-0.01 (-0.3)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)
8	Scenario 8	-7.61 (-46.8)	-0.61 (-4.04)	4.66 (16.2)	5.45 (16.2)	-1.89 (-30.2)	-3.43 (-23.9)	0.68 (15.3)	1.38 (70.9)	1.5 (60.2)	-0.13 (-0.17)

Note: This table depicts the changes in choice probabilities in percentage points (PP) and percent (%) in response to various policy scenarios described in Table 3.C.2. Changes are calculated relative to product choice probabilities in the status quo (current prices and current regulatory landscape). Predictions are performed based on the taste parameter estimates from the latent class logit model, separately for the four identified smoker types.

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Statement of Authorship

I declare herewith that I wrote this thesis on my own, without the help of others. Wherever I have used permitted sources of information, I have made this explicitly clear within my text and I have listed the referenced sources. I understand that if I do not follow these rules that the Senate of the University of Bern is authorized to revoke the title awarded on the basis of this thesis according to Article 36, paragraph 1, litera r of the University Act of September 5th, 1996.

Selbständigkeitserklärung

Ich erkläre hiermit, dass ich diese Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen benutzt habe. Alle Koautorenschaften sowie alle Stellen, die wörtlich oder singemäss aus Quellen entnommen wurden, habe ich als solche gekennzeichnet. Mir ist bekannt, dass andernfalls der Senat gemäss Artikel 36 Absatz 1 Buchstabe o des Gesetzes vom 5. September 1996 über die Universität zum Entzug des aufgrund dieser Arbeit verliehenen Titels berechtigt ist.

Bern, 14. August 2024

Fabienne Loetscher