UNIVERSITY OF COPENHAGEN

Master's Thesis

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Regulating health insurance – Quantitative policy analysis based on a dynamic programming model

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Contents

Abstract

This thesis studies the price dynamics in a model for health insurance where households experience stochastic medical expense shocks. Households are divided into a low-risk or high-risk group for medical expenses. The focus is specifically on private health insurance available on the free market with a monopoly provider. To determine the prices for insurance endogenously, the insurance provider takes the optimal reactions of households into account when choosing the price. The provider sets prices to maximise profits. Demand is then calculated from a dynamic programming choice model where households take the prices as given. This approach allows for a quantitative analysis of changes to the regulatory framework on equilibrium prices and demand for insurance. Starting with a monopolistic insurance provider, multiple policy interventions are discussed. The introduction of perfect competition has the biggest impact on prices, driving down premiums for both risk groups. A ban on price discrimination between high-risk and low-risk agents reduced premiums only for high-risk agents and caused some low-risk agents to opt out. The introduction of a tax penalty on uninsured agents in line with the Obamacare reform successfully increases insurance rates and counteracts adverse selection.

1 Introduction

The availability, cost and quality of health insurance directly affects every American's economic and mental state[1] and thus overall quality of life. In the US, around 29 million non-elderly Americans (11%) were not covered by health insurance in 2019 and about half were uninsured at some point during the 2000s[2]. A lack of health insurance can have severe consequences, both for the individuals and for society. Concerning the effect of health insurance on the general economy, the Council of Economic Advisers for President Obama CEA (2019) predicted that higher coverage rates would increase labour supply, as access to preventive care prevents early drop-outs from the labour market. Additionally, they argue that under-insurance causes the labour market to be sticky and thus less efficient. Aside from labour market frictions, a lack of health insurance is likely to affect peoples' future health conditions, which is supported by Heiss et al. (2009). The authors point out that life expectancy in the US compared to other countries jumps from 25th for the working population to 14th for retirees, who enjoy more universal health coverage. This is in line with findings that around 40% of respondents to a survey from the West Health Institute & NORC (2018) delayed or skipped doctor visits due to high treatment costs and decreased savings or took on debt to pay medical bills. The economic consequences of such behaviour are demonstrated by Jacoby et al. (2001), who use data from bankruptcy courts and find that more than 40% of cases can be related to medical debt, illness, or injury.

Given these significant costs, the US government has tried to intervene in the past, most

[1] Tran et al. (2017)

[2] According to data from the KFF (2020) (Kaiser Family Foundation) and according to the Council of Economic Advisers CEA (2019).

notably through the Affordable Care Act (ACA) in 2010. The ACA standardised and expanded access for health care coverage to low-income households but also included a tax penalty for those that chose not to purchase health insurance (US-Congress (2010)). To intervene in the market by forcing consumers to buy a certain product is evidence on how important increasing insurance coverage was to US policy makers.

This paper contributes to the discussion on how to regulate health insurance by quantifying the relationship between price (or insurance premium) and demand in a model with uncertain medical expenditures. This model will then be used to conduct quantitative policy analysis of a number of interventions and to study their effects on equilibrium prices and demand. The paper proceeds as follows. Section 1 introduces the relevant fields of literature. Section 2 presents a model to determine the optimal reaction of households to changes in the price of insurance, while section 3 focuses on the technical implementation in Python. The results are presented in sections 4 and include an evaluation of changes to the regulatory framework. Section 5 provides a robustness check and section 6 a conclusion.

1.1 Literature review

As this thesis uses numerical methods and dynamic programming models to answer economic questions regarding insurance choices, it builds on both programming and insurance theory literature. The literature about general insurance theory and decision making under uncertainty provides the theoretical framework for how agents behave and how equilibria are formed (Rothschild & Stiglitz (1978)). In insurance theory, moral hazard and adverse selection are two key concepts of interest and the latter will be a primary focus of this study. Following Browne (1992), adverse selection can be described as the tendency of agents with a high risk of experiencing damages to buy more insurance than agents with lower risk. Akerlof (1978), one of the most prominent contributors to the literature about decision making under asymmetric information, demonstrates in his example of used cars how markets collapse due to the selection problem. In a marked with either good or bad quality cars, expected utility maximising bidders will adjust the price they are willing to pay for a car depending on the share of bad products they expect. Sellers of good quality cars will drop out if bids are lower than their reservation price and only bad cars would remain on the market due to selection among sellers. Many studies such as Powell & Goldman (2016), Cutler & Reber (1998) and Bhattacharya & Vogt (2006) find evidence for adverse selection in the market for health insurance, but in contrast to the car example its buyers who self-select. Adverse selection can thus explain the high prices and a lack of insurance coverage, according to Browne (1992). In his example, an insurance provider cannot differentiate between low-risk, normal and high-risk insurance seekers. Naively, it offers an insurance plan favouring the high-risk seekers at a price that makes the plan undesirable for the low-risk group. If the lowest risk individuals opt out, the insurance provider has to raise the premium after overestimating the demand for insurance at the original price. This might cause the medium-risk insurance seeker to opt out next and only individuals with very high risk stay in the portfolio. While the literature usually assumes that the insurance company suffers from imperfect information, risk-types are considered to be public information in this study. A pooling equilibrium (all types chose the same plan) can only be achieved by a regulatory intervention.

The second field of literature provides proven methods for solving dynamic problems. Employing dynamic programming models to Economics has been a common practice over the last decades. A prominent example is Rust (1987), who models the engine replacement decision of a bus company as a trade-off between reducing maintenance costs and preventing engine failure. Brito (2008) can be considered for a more general summary of dynamic programming applications. Keane et al. (2011) summarise contributions to the literature about discrete choice models, focusing on labour supply and job search problems. As the insurance decision in this study will be discrete (either yes or no) and combined with a continuous choice over consumption, the focus will be on discrete-continuous choice models. The methods used for solving this type of model are well established in the literature and I rely on these results for both the model section as well as the technical implementation. More specifically, this paper uses a method called Value Function Iteration (VFI), for reference see among others Santos (1999). Due to the high computational costs of VFI, a more recent string of literature evolved around optimising and generalising the so-called Endogenous Grid Method (EGM) by Carroll (2006) to be applicable to discrete choices, most notably Fella (2014), Iskhakov et al. (2015) and Druedahl & Jørgensen (2017). While the EGM is not used, some features from the approach of solving and simulating in this paper build on their work. There also exists a wide range of literature that, like this thesis, combines dynamic programming and insurance theory. Heiss et al. (2009) study government interventions to counter adverse selection at the example of Medicare enrolment. They find that direct subsidies of premiums seemed to have a bigger effect than a late enrolment penalty on young adults. French et al. (2016) study the incentives created by the ACA reform, namely a Medicaid expansion and premium subsidies. Their research focuses on labour supply of elderly Americans close to retirement. Kotlikoff (1989), De Nardi et al. (2006) and Hsu (2013) analyse the effect of health insurance on household savings under the presence of stochastic medical expense shocks. This paper contributes to the literature by proposing a numerical approach for an endogenous determination of equilibrium prices. This is achieved by combining a classic dynamic discrete choice model for household behaviour with an insurance company as an additional decision maker. To model the insurer's objective function is a feature from ruin theory. The focus of this literature is to minimise the probability of ruin for the insurer and often builds on so-called Cramér-Lundberg models where claims arrive from a Poisson process[3]. The company often faces the problem of how to hedge the risk from claims by optimising the investment of its revenue into the stock market (which is disregarded here).

As this paper refers to the optimal prices of insurance as the "general equilibrium" (GE), it should be noted that other dynamic programming literature on GE models exists – often in macroeconomic context. Simply speaking, a GE has to achieve market clearing (e.g., in the goods, labour and capital markets). Equilibrium factor prices are found by substituting the first order conditions that constitute optimal behaviour of households and firms into each other[4]. Due to the lack of a closed form solution, I refer to the general equilibrium as the price that maximises the firm's objective (supply) while taking optimal reactions by households into account (demand).

[3] Kasumo (2019), Asmussen et al. (2013) and Christensen et al. (2021) contribute to this literature.

[4] For a more complex example of micro-founded macroeconomic GE models, the interested reader is referred to the research on Heterogeneous Agent New Keynesian (HANK) models by Auclert et al. (2020) or Kaplan et al. (2018) as examples.

2 Model

The US health insurance market provides coverage in four ways. Following NCSL (2021), (i) Medicare is a government funded program providing basic universal care for the elderly population (14% of the population). (ii) Medicaid is a public program designed to provide coverage to low-income household (20%) and is subject to an asset and income test. Everyone not covered by Medicaid or Medicare is (iii) insured through their employer (50%) or (iv) can purchase a private plan on the free market (6%). Due to the complexity caused by the mix of insurance forms, the model applied in this paper is restricted to only consider private market provision (iv). This section starts with presenting the households' decision problem and continues with describing the solution method for discrete-continuous choice models from the literature.

A discrete-continuous choice model of insurance

Consider a society with N single agent households and one private company referred to as the insurance provider. Agents can be of two health types, one with a low risk of needing medical treatment and one group with a high risk of medical treatment. The identifier for the risk type is θ, which is constant over time. It is assumed that all agents know their own type but not their specific medical expenses that realise in the future. The insurance provider can observe the health type of potential insurance takers and offers an insurance plan that is valid for a certain period t at a price $(\lambda^{\theta=0}, \lambda^{\theta=1})$. Each period, the agents face two choices: How much to consume (c) and whether to buy health insurance, $z \in (0, 1)$. If health insurance is purchased by an agent, 100% of her medical expenses from the period will be paid by the provider.

As a consequence, agents maximise a value function with respect to two variables c and z. To solve the described problem, I rely on established results from the literature. First, note that the same structural choice is repeated each period and that the need to incorporate how the choice of today affects the choice of the future makes this a dynamic problem.

$$V_t(m_t, \theta, \epsilon_t^0, \epsilon_t^1) = \max_{z_t \in \{0,1\}} v_t(m_t, \theta, |z_t) + \sigma_\epsilon \epsilon_t^{z_t} \tag{1}$$

$$\epsilon_t^0, \epsilon_t^1 \sim \text{Extreme Value type 1}$$

$$v_t(m_t, \theta | z_t) = \max_{c_t} \frac{c_t^{1-\rho_\theta}}{1-\rho_\theta} + \beta \mathbb{E}_t \left[V_{t+1}(m_{t+1}, \theta, \epsilon_{t+1}^0, \epsilon_{t+1}^0) \right] \tag{2}$$

$$s.t.$$

$$m_{t+1} = (1+r)(m_t - c_t - \underbrace{z_t \lambda^\theta}_{\text{premium}} - \underbrace{(1-z_t)\chi}_{\text{penalty}}) + \underbrace{p_{t+1}^\theta}_{\text{income minus medical expenses}} \tag{3}$$

For a given price pair (λ^0, λ^1), this type of problem can be solved using Bellman (1957)'s principle of optimality, which implies that the optimal solution to a problem can be found from the solutions to its sub-problems. Equation (2) represents the Bellman equation for the dynamic choice problem and thus describes the recurring sub-problem[5]. The second aspect to note is that agents maximise a discrete in z_t and a continuous choice in c_t at the same time, as (2) can be substituted into (1). In the literature, the approach to this type of decision problem is to consider the discrete choice as given and calculate the value from consumption once for each discrete choice option. In this case,

[5]Equation (2) contains itself through V_{t+1} as $V_{t+1}(m_{t+1}, \theta, \epsilon_{t+1}^0, \epsilon_{t+1}^0)$ itself can be replaced according to equation (1) but with increasing the time subscript by 1 period. It thus implicitly contains $V_{t+2}, V_{t+3}, \ldots$.

equation (2) can be interpreted as the choice-specific value function given either $z_t = 0$ for $z_t = 1$. This results in two separate problems that are only maximised with respect to the continuous choice c. Iskhakov et al. (2015) introduce the extreme value type 1 distributed taste shocks to deal with problems caused by the discrete choice, which will be discussed in section 3.1.

Equation (3) defines the transition function for cash on hand m and incorporates the insurance decision through both savings in (4) and future income in (5) from below. The terms "premium" and "price" for insurance are used synonymously.

$$a_t = m_t - c_t - z_t \lambda^\theta - (1 - z_t)\chi \geq 0 \tag{4}$$

$$p^\theta_{t+1} = \begin{cases} y & \text{if } z_t = 1 \\ y\zeta^\theta_{t+1} & \text{if } z_t = 0 \end{cases} \tag{5}$$

$$0 \leq c_t \leq m_t - z_t \lambda^\theta - (1 - z_t)\chi$$

$$\zeta^0_t \sim U(0, 1), \quad \zeta^1_t \sim U(0.5, 1)$$

$$\rho^0 > \rho^1, \quad \theta \in (0, 1)$$

Assets are in equation (4) defined as the beginning of period cash m subtracted by consumption and the costs for buying insurance if $z_t = 1$, or by subtracting a tax penalty χ[6] if not. The model thus nests the benchmark case where χ is set to 0. The insurance provider can discriminate between risk-types by offering different prices to different types λ^θ. By assumption, assets cannot be negative and households can't take

[6]The purchase mandate from the ACA reform mentioned before.

on debt. Finally, equation (5) describes the income transition process. Each period, every agent gets a fixed income $y = 1$ and suffers from expenditures due to stochastic medical expenses. This shock to income is denoted as ζ^θ and is health type depended. ζ denotes what share of income is left after medical expenses have realised. As implied by equation (4), agents can insure themselves against a reduction of future income by purchasing health insurance. An insured agent will be guaranteed a future income of y while an agent without coverage will be subject to the income shock. From the distribution of ζ^θ, it follows that the risk of losing income is structurally higher for high-risk types $\theta = 0$. If unlucky, a high-risk agent can lose 100% of her income if $\zeta^\theta = 0$. For low-risk agents, the maximum possible income reduction is restricted to 50% by design.

2.1 Solving the model given exogenous insurance prices

For solving the model, I follow the approach from the literature on discrete-continuous choice models and value function iteration[7].

First, note that equation (2) can be rewritten by defining the discounted continuation value $w_t(m_t, \theta | z_t) = \beta \mathbb{E}_t \left[V_{t+1}(m_{t+1}, \theta, \epsilon^0_{t+1}, \epsilon^0_{t+1}) \right]$:

$$v_t(m_t, \theta | z_t) = \max_{c_t} \frac{c_t^{1-\rho_\theta}}{1-\rho_\theta} + w_t(m_t, \theta | z_t) \tag{6}$$

[7]Especially the technical appendix of Jakobsen et al. (Forthcoming).

This discounted continuation value can be stated as a three-dimensional integral over the two taste shocks $\epsilon_t^{z_t}$ and the shock to medical expenses ζ^θ.

$$w_t(m_t,\theta|z_t) = \beta \int\int\int \left[V_{t+1}(\bar{m}_t + \bar{p}_{t+1}\zeta^\theta_{t+1}, \theta, \epsilon^0_{t+1}, \epsilon^1_{t+1}) + \sigma_\epsilon \epsilon^{z_t}_{t+1} \right] g(\epsilon^0) g(\epsilon^1) g(\zeta^\theta) d\epsilon^0 d\epsilon^1 d\zeta^\theta$$

Because ϵ_t^0 and ϵ_t^1 are Extreme Value type 1 distributed, the expected value with respect to these two shocks has a solution in closed form. Following the discussion about taste shocks from Iskhakov et al. (2015), this closed form solution is given by the *logsum* function.

$$w_t(m_t,\theta|z_t) = \beta \int \left[logsum(v_{t+1}(m_{t+1},\theta|z_{t+1})) \right] g(\zeta^\theta) d\zeta^\theta \tag{7}$$

After defining $EV_t(m_{t+1},\theta)$ as the result of the *logsum* function, $w_t(m_t,\theta|z_t)$ can be reduced to equation (9):

$$EV_t(m_{t+1},\theta) = \sigma^\epsilon log\left(\sum_{i\in\{0,1\}} exp^{\frac{v_{t+1}(m_{t+1},\theta|z_{t+1}=i)}{\sigma^\epsilon}} \right) \tag{8}$$

$$w_t(m_t,\theta|z_t) = \beta \mathbb{E}_t \left[EV_t(m_{t+1},\theta) \right] = \beta \int \left[EV_t(\bar{m}_t + \bar{p}_{t+1}\zeta^\theta_{t+1}, \theta) \right] g(\zeta) d\zeta \tag{9}$$

This one-dimensional integral can be approximated by discretizing the integral given K^{ζ^θ} Gauss-quadrature nodes.

$$\approx \beta \sum_{k^{\zeta^\theta}}^{K^{\zeta^\theta}} \omega_{k^{\zeta^\theta}} \left[EV_t(\bar{m}_t + \bar{p}_{t+1}k^{\zeta^\theta}, \theta) \right] \tag{10}$$

The model is solved by value function iteration (VFI) as described in section 3.

2.2 General equilibrium: The insurance company's choice problem

Recall that the model proposed so far provides optimal household reaction but only holds for the given exogenous pair of prices (λ^0, λ^1). This is in the following referred to as the *"HH model"*. In this section, this HH model will be expanded to allow for an endogenous determination of equilibrium prices by introducing a single insurance company as an additional decision maker. The insurance provider will set prices (λ^0, λ^1) and households are treated as price takers in the sense that each agent does not expect his individual decision on insurance to influence the overall pricing decision of the insurance provider. The objective is to find prices $(\lambda^{0*}, \lambda^{1*})$ that are optimal from the insurance provider's perspective while taking the optimal reactions of all households into account. I thus refer to these optimal price pairs as the "general equilibrium" price of insurance while being aware that the proposed approach is a heuristic and numerical and not an analytical solution to the decision problem.

The decision problem for the insurance provider is defined by an objective function, in this case its profit function depending on revenue and costs. As usual, the insurance company maximises its profits.

$$U^{company}(R, C) = \max_{\lambda^0, \lambda^1} R\Big(\lambda^0, \lambda^1, z^{0*}(\lambda^0), z^{1*}(\lambda^1)\Big) - C\Bigg(O, z^{0*}(\lambda^0), z^{1*}(\lambda^1)\Bigg) \tag{11}$$

The insurance market is special because in contrast to classic GE models, no physical good is produced. The production function is reduced to operating costs O and set to zero by assumption. Supplying insurance services to one additional customer costs nothing except for the obligation to pay potential claims. Both revenue and costs depend on the chosen prices as well as the resulting optimal reaction by the households which constitutes demand (denoted as $z^{\theta *}$ in equation (11)). The optimal demand as a reaction to the chosen prices, $z^{\theta *}(\lambda^{\theta})$, can thus be calculated from the HH model described in section 2 by treating (λ^0, λ^1) as exogenous. The prices are paid to the insurance company as revenue, claims are reported to the insurer by the covered agents once they suffer a medical expense shock. Assuming the company does not fight moral hazard, it will honour all claims made. Revenue and costs can then be determined by calculating the expected demand as well as expected claims given chosen prices.

$$R_t = \sum_{\theta=0}^{1} \left(\lambda^{\theta} \sum_{i=1}^{n} z^*_{i,t}(m_{i,t}, \theta) \right) \tag{12}$$

$$C_t = O_t + \sum_{\theta=0}^{1} \left(\sum_{i=1}^{n} z^*_{i,t}(m_{i,t}, \theta) y \frac{1}{n} \sum_{i=1}^{n} (1 - \zeta^{\theta}_{i,t+1}) \right) \tag{13}$$

where $y(1-\zeta^{\theta}_{i,t+1})$ are claims from agent i and $z^*_{i,t}(m_{i,t}, \theta)$ is a binary insurance decision.

When choosing the optimal price, the insurance provider does not yet know what the future claims of the agents will be. But it knows the health type of all agents under coverage as well as the distribution of shocks to each type from equation 5. Define $\sum_{i=1}^{n} z^*_{i,t}(m_{i,t}, \theta = 0)$ as the number of high-risk types and $\sum_{i=1}^{n} z^*_{i,t}(m_{i,t}, \theta = 1)$ as the number of low-risk types in the portfolio of the insurance provider. Due to the known distribution of the shocks, the insurance company knows that expected claims, $\frac{1}{n} \sum_{i=1}^{n} (1 - \zeta^{\theta}_{i})$, of a high-risk type are 0.5 (sample mean of $\zeta^{\theta=0}$ is 0.5), while expected claim of a low-risk type will be 0.25 (sample mean of $\zeta^{\theta=1}$ is 0.75), as long as the sample is large enough. The company can therefore estimate the profit it expects to make when choosing a price tupel (λ^0, λ^1) only from knowing the demand for insurance at that price. An algorithm will be proposed in the next section on how the HH model introduced earlier in section 2 can be used to find the equilibrium.

A number of important terms will be used throughout the rest of the paper. I define **high-risk types** as agents with $\theta = 0$, **low-risk types** as agents with $\theta = 1$, **VFI** as the Value Function Iteration method, and **purchase mandate** as the tax penalty for uninsured agents χ. **Benchmark** or pre-ACA will refer to the model specification without a tax penalty $\chi = 0$ and **post-ACA** will refer to the model specification including the mandate parameter $\chi = 0.1$.

3 Technical Implementation

The model was implemented in Python and the code has been submitted as part of this thesis. To structure the technical discussion, the approach can be broken down into three steps. In step 1, the HH model from section 2 is solved in infinite time horizon with VFI and step 2 describes how to simulate data from the model. Finally, step 3 introduces the insurance provider following section 2.2 and presents an algorithm to find the general equilibrium prices endogenously.

3.1 Solving the model with infinite time horizon

In general terms, solving the model means calculating solution arrays for utility $V[z, \theta, m]$ and consumption $C[z, \theta, m]$ for each possible combination of state variables (z, θ, m). Think of these arrays as a collection of optimal solutions given a certain state. These arrays will later be needed to assess the preferences of the simulated agents: If the individual-specific values for z, m and θ are known for a given agent i, a simple look-up in the solution array will tell the valuation or consumption calculated by the model and thus, allow for a comparison of e.g., $V[z = 0, \theta_i, m_i]$ vs. $V[z = 1, \theta_i, m_i]$. Algorithm 1 illustrates the VFI routine[8]. The model will be solved with an infinite time horizon, so the solution arrays V and C do not have a dimension for time t. The idea behind an infinite horizon is to find a unique fixed point of V. For the proof of the existence of such a fix point consider Stokey (1989). To find the fixed point of V, the model will be run in a loop, evaluating the difference (Δ) between the value arrays $V[z, \theta, m]$ and $V\_next[z, \theta, m]$ after each iteration. V_next corresponds to the value calculated in the

[8]For reference, see e.g., Santos (1999).

previous iteration making this a potentially endless backwards induction. To prevent the loop from running forever, a stopping criterion is defined (see algorithm 1, line 22) which terminates the loop when the model converged, i.e., when Δ is lower than a certain tolerance. The main drawback of using the VFI method is that it is very time consuming. In each iteration of the loop, the value function has to be evaluated and the optimiser has to be called for each combination of state variables. Nevertheless, the method was chosen due to the ability to control the boundaries in the optimisation of c. From equation (4) it follows that c has an upper bound at $m_t - z_t\lambda^\theta - (1 - z_t)\chi$. However, applying a restriction on c alone does not secure the constraint $a \geq 0$[9]. To handle this issue, the following assumption will be made:

Assumption 1 *If an agent can't afford the premium ($\boldsymbol{m} < \lambda$), she does not face a discrete choice but will always be uninsured and the mandate will not apply.*

As a consequence, the solution array $V[z = 1, \theta, m]$ will not be defined for $m < \lambda$.

Running the model with the parameters specified in appendix A takes 164 seconds and 69 iterations to successfully convergence. For a given price (λ^0, λ^1) of (0.4, 0.3), the choice-specific value functions are reported in figure 1 below. The low-risk agents (right panel) seem to always prefer not to be insured for all values of m while high-risk agents prefer not be insured for low values of m but change preferences shortly after $m > \lambda^0$.

[9]When calculating the value of being insured taking z=1 as given, $m_t - z_t\lambda^\theta - (1 - z_t)\chi$ would still be negative for very low values of m, even if $c = 0$. The lowest value in $\mathcal{G}_m$ is $1e^{-6}$ and it is easy to see that for basically any positive prices for insurance λ^θ, assets would be negative because such an agents would simply be to poor to pay for insurance. The same issue would arise in the case where $z = 0$ is given and the tax penalty applies ($\chi > 0$).

Algorithm 1: Routine for solving the discrete-continuous choice problem with VFI

Input: $\mathcal{G}_m$, $tol = 1e^{-1}, max\_iter = 5000, shape = (Nz, N_\theta, Nm) = (2, 2, 100)$

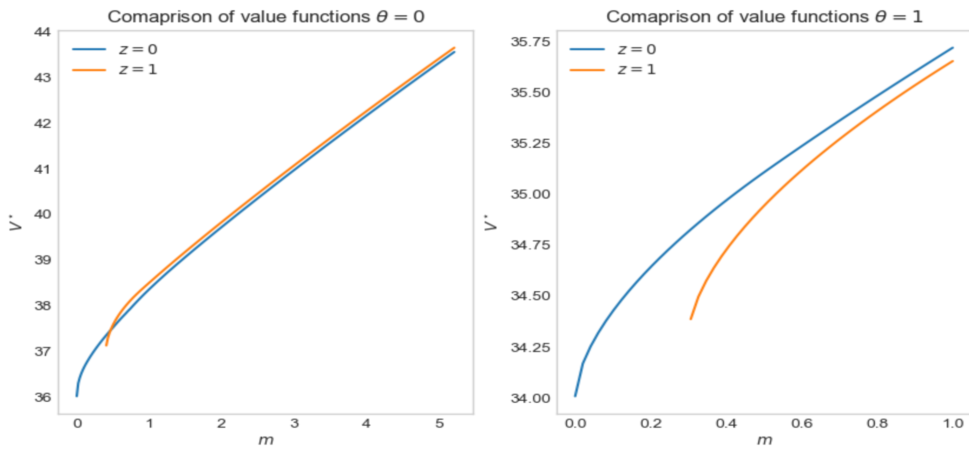
Output: Arrays for V[2,2,100] and C[2, 2, 100]

```
#Initialise before 1st iteration;
for z in (0,1) do
    for θ in (0,1) do
        for i_m, m in G_m do
            C[z, θ, i_m] = m;
            V[z, θ, i_m] = u(C[z, θ, i_m], ρ);

#Find fixed point for V;
it = 0;
delta = 1000;
while delta ≥ tol and it < max_iter do
    V_next = V.copy() # V from previous iteration
     for z in (0,1) do
        for θ in (0,1) do
            for i_m, m in G_m do
                upper bound = get_assets(0,m,z,θ) # set c = 0 for upper bound;
                # call the optimizer;
                obj_fun = - value_of_choice(x=c,z,m,θ,G_m,V_next);
                res = optimize.minimize_scalar(obj_fun, bounds=[0,upper bound]);
                V[z, θ, i_m] = -res.fun # assign value;
                C[z, θ, i_m] = res.x # assign optimal consumption;

    # update delta and it;
    it += 1;
    delta = max(abs(V - V_next)) # calculate absolute maximum distance
```

Figure 1: Choice-specific value function given prices (λ^0, λ^1) of (0.4, 0.3)



The blue and orange lines represent the choice-specific value functions $v_t(m_t, \theta, |z_t)$ from equation (2), which are concave. When optimising over z in equation (1), the optimal value function $V_t(m_t, \theta = 0, \epsilon_t^0, \epsilon_t^1)$ has a kink where the orange and blue lines intersect. Before the decision over z, the value function is therefore not a smooth function. To handle this issue, Iskhakov et al. (2015) introduce so called taste shocks to the model. The authors show that these kinks would be carried over in time when iterating backwards. They also show that taste shocks in combination with other stochastic shocks (here ζ) can cure this issue by smoothing the value function[10]. A key property of these shocks is that the probability to choose any option is always greater than zero[11]. The authors argue that this can be seen as accounting for unobserved characteristics other than the state variables in the model. Consequently, some low-risk agents will choose insurance in this study even if the right panel on figure 1 shows that it is mathematically sub-optimal[12].

[10]Iskhakov et al. (2015), Figure 2.

[11]See appendix B, page 55

[12]Because the difference in $V[z = 0, \theta, m]$ vs. $V[z = 1, \theta, m]$ is larger for them, they will however be

3.2 Numerical simulation

After the HH model converged, a panel of insurance decisions can be simulated. 10.000 agents are "born" with individual values (θ_i, m_i). From this initial point, the agents' state will be simulated forward in time with an infinite horizon[13]. For each iteration, decisions are simulated by using the model solution to compare the choice options. The method consists of four main steps which are presented in appendix B, algorithm 3[14]. In short, the method can be summarised as follows: First, take the current state variables of each agent and get the value and consumption from the pre-computed V and C from the VFI. Because these solutions were only calculated specifically for the 100 points in $\mathcal{G}_m$, the values have to be interpolated for agents whose current state m is between two grid points. Next, the choice probabilities, Pr(z=0$|m_i, \theta_i$) and Pr(z=1$|m_i, \theta_i$), are calculated. Step 3 translates the probabilities into a binary decision which is necessary because probabilities alone would not be sufficient to simulate actual decisions of agents. A random number is compared with the calculated probability of not choosing insurance. If that number is lower, the agent does not buy insurance. If it is higher, the agent decides to buy health insurance. Lastly, given agent i's decision over z, her resources transition into the next period and the process is repeated.

Methodically, the question is how to determine when to stop this infinite horizon forward simulation. The chosen approach is similar to the stopping criterion in the VFI algorithm and the idea is to terminate once the distribution of m stabilises in the sense

less likely to do so than high-risk types.

[13] Similar to the model, the simulation also has to be initialised with some parameters also reported in appendix B.

[14] The code for implementing the simulation is inspired by lecture material from the course on "Introduction to Dynamic Programming" at Københavns Universitet by Thomas Jørgensen and Bertel Schjerning, taken in spring 2021.

that changes form iteration to iteration are only minor. For a more in-debt description of the stopping criterion see appendix C. The final output of the simulation method are two $(Nx1)$ arrays containing consumption and insurance choices for each agent in the last period before the simulation was terminated.

3.3 Algorithm to find general equilibrium prices

Building on section 2.2, equilibrium prices $(\lambda^{0*}, \lambda^{1*})$ are found by following algorithm 2, which can be summarised as a grid search across a pre-defined range of price candidates. The whole approach resembles a technique called hyperparameter tuning often used when fitting neural networks or other machine learning models, e.g., in Gu et al. (2020). A model is fitted multiple times for different values of a parameter and eventually, the model specification with the best performance is selected. In this case and in contrast to ruin theory literature, the insurance provider treats its price optimisation decision as a hyperparameter tuning problem. The fitted parameters would be (λ^0, λ^1) and the performance criterion would be the profit of the insurance provider. Thus, the choice of prices is endogenous in the sense that the insurer selects the most attractive candidate out of all evaluated options. Demand can be interpreted as the aggregated individual choices from the simulation which itself is based on the solution arrays from the VFI. These simulated choices constitute the optimal reaction of households to the proposed price pair. Of course, there is a trade–off between computational time and precision. If the set of potential price candidates is too limited, the resulting profits could e.g., all be negative. On the other hand, increasing the number of candidates will increase computation time exponentially. To balance this trade-off, the grids $\mathcal{G}_{\lambda^0}$ and $\mathcal{G}_{\lambda^1}$ will be restricted to contain 10 values between 0.3 and 0.8. This range is of course somewhat arbitrary. Because the parameter range only affected results in sections 4.1.3 and 4.2.3, these sections will discuss the robustness of the results.

Algorithm 2: Heuristic to determine price of insurance endogenously

Input: V[2,2,100] and C[2,2,100] from VFI, $\mathcal{G}_{\lambda^0}$ with N_{λ^0}, $\mathcal{G}_{\lambda^1}$ with N_{λ^1}

Output: result matrices with shape (N_{λ^0}, N_{λ^1})

# initialise output object;
profit_matrix = zeros(shape);
for *i, x in* $\mathcal{G}_{\lambda^0}$ **do**
    for *j, y in* $\mathcal{G}_{\lambda^1}$ **do**
        # initialise the model from section 2 but overwrite premium parameters;
        λ^0 = y;
        λ^1 = x;
        # solve and simulate model for given price combination (x,y);
        V, C^*= solve_VFI(λ^0, λ^1);
        z^0*, z^1*= simulate($\lambda^0, \lambda^1, V, C^*$) # z* is demand given price;
        # Get profits given price combination;
        Calculate the resulting number of people in the 2 portfolios (one for each θ);
        Calculate revenue R from price vector (λ^0, λ^1) and from the number of people under coverage;
        Calculate costs C from the number of people under coverage and from the sample average claims per type;
        Calculate the profit as $\pi = R - C$;
        # Assign profit to matrix at price combination (x,y);
        profit_matrix[i, j] = π
Return profit_matrix;
Follow similar logic to calculate other results such as the insurance rate

4 Results

This chapter will first present the results from running the model under benchmark specifications in section 4.1. These findings will then be compared to results from introducing the purchase mandate from the ACA reform as a demand side intervention in section 4.2. Both will contain two subsections discussing a ban on price discrimination and competition regulation as potential supply side interventions. Lastly, section 4.3 investigates the effect of a system switch from private insurance provision to a tax funded and mandatory public system.

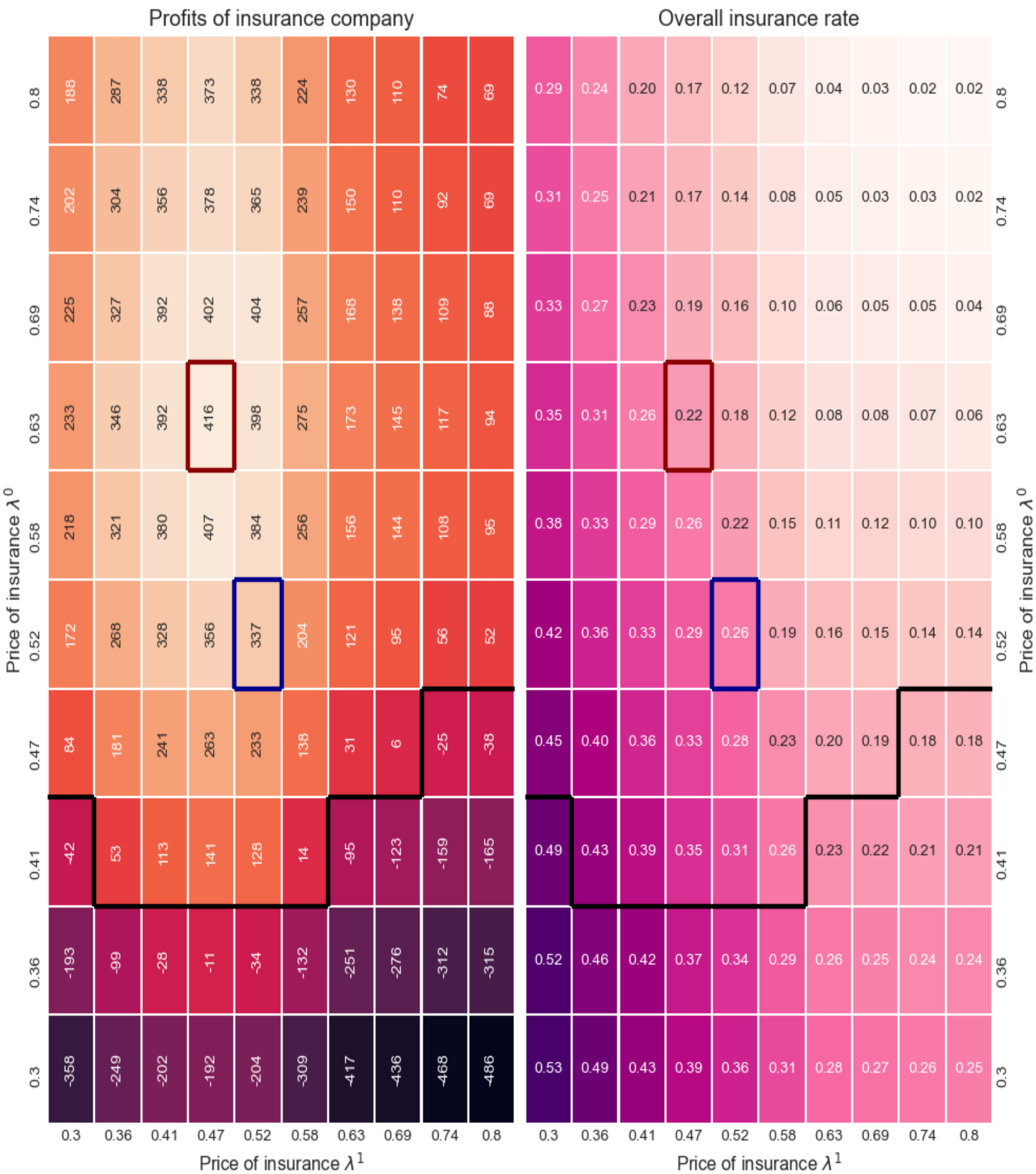
4.1 The benchmark: Equilibrium prices without a tax penalty

The approach described in section 3.3 will require the model to be solved and simulated 100 times, once for each combination of the two vectors $\mathcal{G}_{\lambda^0}$ and $\mathcal{G}_{\lambda^1}$. The output from this procedure, and thereby also its main results, will be a 10x10 matrix of profits[15]. Figure 2 reports the generated data that can be used to study the relationship between price, demand, and profits in the benchmark model. The figure contains two panels both with insurance prices λ^1 as the x-axis and λ^0 as the y-axis. The values displayed inside the left panel of the figure represent the profit or loss the company would achieve given a certain combination of (λ^0, λ^1). The right panel shows the corresponding demand for insurance as a percentage of agents that take insurance. An equilibrium candidate will in the following be denoted as the pair of coordinates ($\mathbf{y} = \lambda^0$, $\mathbf{x} = \lambda^1$) so the price for high-risk types (on y-axis) is always reported first. The insurance rate represents the

[15] These are the profits from the simulation period in which the distribution of m was assumed to have stabilised.

demand across both types, or in other words, the optimal reaction of households to the price pair.

Figure 2: Profit and demand matrices



Red square marks equilibrium for monopoly competition from 4.1.1, blue square marks no discrimination equilibrium from 4.1.2 and black line marks zero profit line for 4.1.3. (To go back to table 2 (page 36), click here.)

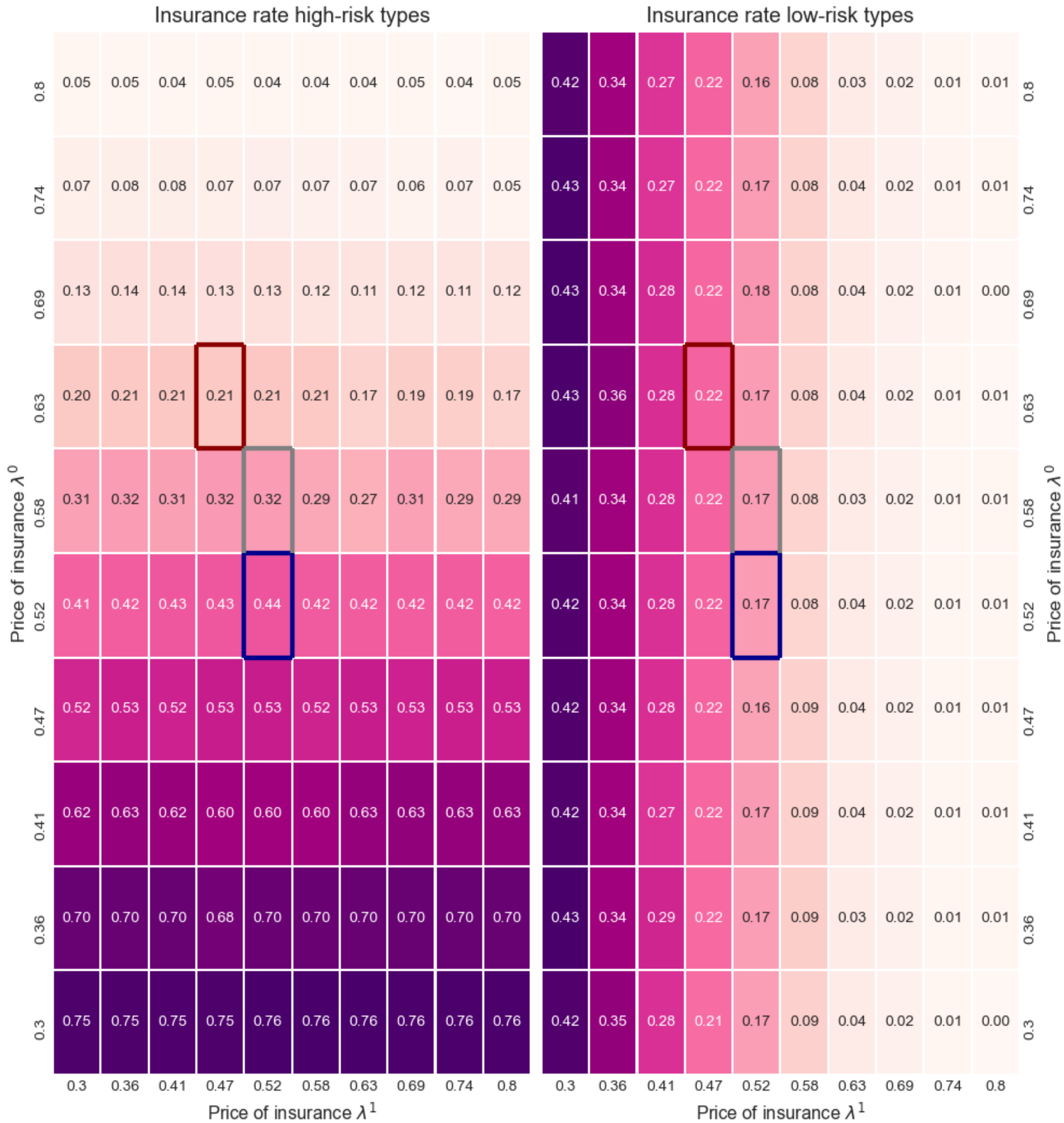
4.1.1 Profit maximising equilibrium under monopoly competition

Without any political interference, the monopoly insurance provider's problem is simply to maximise profits as in equation (11). The key takeaway here is that the heat map in figure 2 for profits looks like a topographic map of a mountain viewed from above with a peak of 416. The darker colours indicate that profits fall towards the corners. A profit maximising equilibrium price of a monopolist (λ^{0*}, λ^{1*}) is found at the red marked field ($y = 0.63$, $x = 0.47$) and results in an insurance rate of 22%.

Next, figure 3 reports the type-specific demand for insurance. The left panel shows insurance rates among agents with a high risk factor while the right reports insurance rates for low-risk types. Clearly, the colour transition on the left side is vertical but horizontal in the right panel. This confirms that demand for insurance of the high-risk types is independent of the price for insurance of the low-risk type (x-axis) and vice versa. Note that minor fluctuations are caused by different conversion speeds of the model for different price combinations[16]. At the found equilibrium from above, again marked red, the type-specific demand is relatively similar and even slightly higher for low-risk types. Based on established results from the literature, higher risk agents would be expected to buy more insurance than low-risk agents, which is not the case at this equilibrium. However, the insurance provider was specifically allowed to set separate prices for the two groups and assumed to be able to differentiate between the types. Because information disadvantage of the insurance provider is the main cause of adverse selection, it is not surprising that it does not seem to be a concern here.

[16] The number of iterations to reach convergence in the value function was between 67 and 75 while the number of iterations needed for the distribution to stabilise was between 4 and 37.

Figure 3: Type-specific insurance rates



Red marks equilibrium for monopoly competition from 4.1.1, grey marks the Pre-ACA counterfactual in table 2 in 4.2.1. Blue marks no discrimination from 4.1.2.
(To go back to table 2 (page 36), click here.)

Figure 3 can also be used to calculate the price elasticity of demand for each risk type. The elasticity is defined as the percentage change in demand caused by a 1% increase in price and is by nature negative (for regular goods). This relationship between prices and demand is not necessarily constant and the 10x10 matrices allow for 9 separate evaluations of how much the price increase between two points in the price grid reduces demand. Figure 4 shows that an increase in price (grey) causes relatively strong reductions in demand of both types and that low-risk agents react stronger (blue) than high-risk types (red). From panel (b) follows that increasing a low price by 1% causes a similar decrease in demand by around 1% but when an already high price is increased, demand reacts even stronger. For higher prices, demand converges to zero for both groups so the data become less meaningful for high values on the x-axis in the figure.

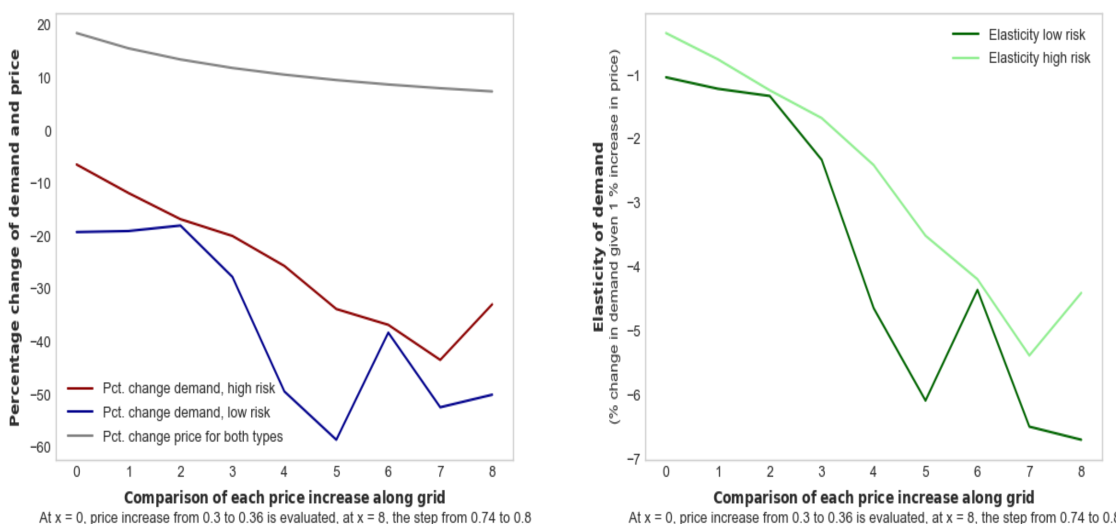


Figure 4: Price elasticity of demand

These findings offer some general insights regarding the relationship between prices and demand. This setup also allows for an interesting analysis of how the equilibrium depends on certain features of the model. Therefore, the rest of section 4 will discuss selected interventions and their effect on the equilibrium.

4.1.2 The effect of eliminating price discrimination on equilibrium prices

The first question of interest is to what extend the ability of the insurance provider to discriminate between the types affects equilibrium outcomes. It is common for insurance providers to offer different plans at a different price to different groups of insurance takers. To design these plans, it is in their interest to use information about e.g., a client's age, smoking behaviour or existing medical conditions. In this simplified model, only one factor θ affects health outcomes and agents can't be excluded from coverage. A ban on price discrimination means the regulator forces the provider to set $\lambda^0 = \lambda^1$. This can be interpreted as regulation on product design and is therefore a supply side intervention. In figure 2, the bottom-left to top-right diagonal of the left panel represents all profits that can be achieved by setting $\lambda^0 = \lambda^1$ and figure 5 plots the two-dimensional data obtained from interpolating along this diagonal. A few things can be concluded here. At first, the equilibrium price is now at the blue marked field (0.52,0.52) in figure 2 which results in an insurance rate of 26%. The monopoly profits at the peak are now at 337 which is around 20% lower compared to the profits with price discrimination. If compared to the previous equilibrium of ($\lambda^0 = 0.63$, $\lambda^1 = 0.47$) marked in red, preventing price discrimination favours the high-risk agents. These now pay 17% less for insurance but low-risk agents pay 10% more. At the new equilibrium (0.52, 0.52) and following figure 3, 44% of high-risk agents buy insurance at this price but only 17% of low-risk agents do (compared to 21% and 22% before). As expected and consistent with the literature, some of the low-risk type agents opt out of insurance and high-risk agents buy more insurance. A ban on price discrimination causes adverse selection but not to a degree where the pooling equilibrium collapses. Globally, it is hard to argue that preventing price discrimination produces a more desirable equilibrium because not all agents experience an improvement. While the uniform price of 0.52 is lower than the average price with discrimination of 0.55, two thirds of agents would end up paying more for insurance than before[17]. The overall insurance rate is increased but the magnitude of the increase is relatively small at 4 percentage points.

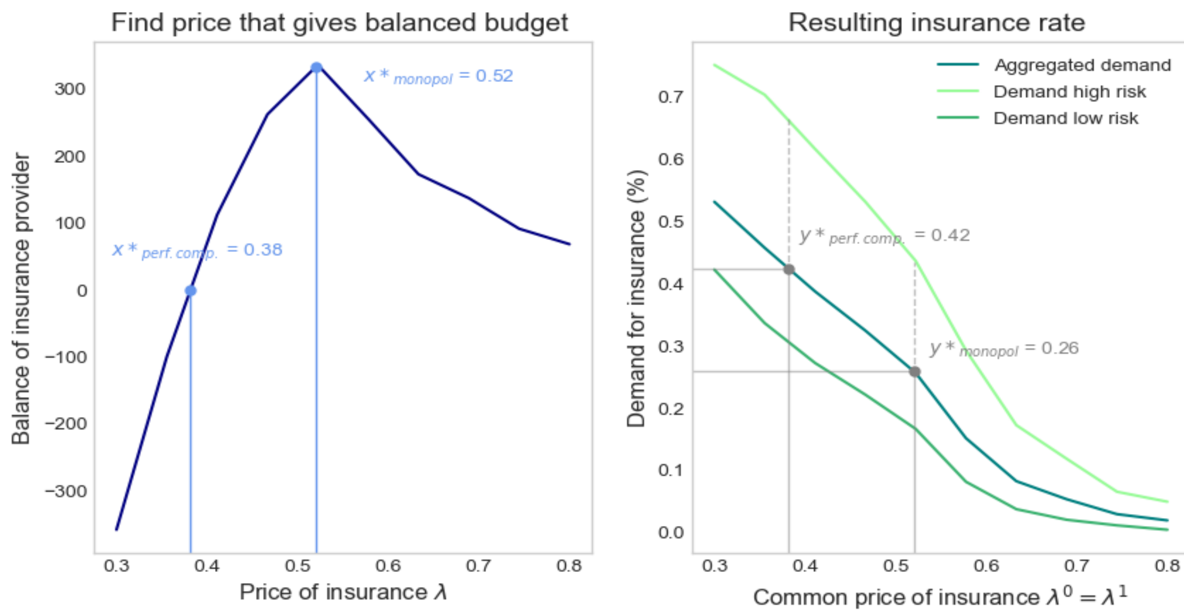


Figure 5: Optimal price for insurance without price discrimination $\lambda^0 = \lambda^1$

4.1.3 The effect of perfect competition on equilibrium prices

So far, the insurance provider was considered to be a monopolist. Thus, a second question of interest is how competition can affect equilibrium prices. Any regulation designed to increase competition is again a supply side intervention. It is well known that the assumption of perfect competition among suppliers usually implies that each company makes a profit of zero. Otherwise, a new competitor would enter the market

[17]From appendix A, it can be seen that the share of low-risk types is 2/3.

to slightly undercut the price of any profitable company in the market. Due to the relatively big difference between the grid points in $\mathcal{G}_{\lambda^0}$ and $\mathcal{G}_{\lambda^1}$, the search is not precise enough for one proposed price combination to actually result in profits of exactly zero. But for every two fields of the left panel of figure 2 in between which profits switch sign, a price in between them exists for which $Revenue = Costs$ holds. In other words, an infinite number of combinations between (λ^0, λ^1) results in zero profits. Fields in figure 2 coloured in red (low but positive) or light purple (low but negative) indicate profits close to 0 and are marked by the black line.

However, the found optimal price pairs result in different levels of demand for insurance. If the objective function of the insurance company only considers profits, it is indifferent between all these points. However, if the regulator forces the provider to take the insurance rate into account, some equilibria should strictly dominate others. Given the discussion about personal and economic costs of under-insurance from the introduction, one could assume that the regulator wants insurance rates to be maximised. Consequently, the most desirable zero-profit price pair (λ^{0*}, λ^{1*}) is the one that is furthest in the bottom left corner where both λ^0 and λ^1 are lowest. As demand for insurance decreases with its price, the highest demand for insurance will also be found at the bottom left corner. Figure 6 compares the data obtained by interpolating along each of the first three columns of the left panel in figure 2. Each line in the left plot shows the interpolated profit function $\pi^{firm} = f(\lambda^0|\lambda^1)$ for a given value of λ^1. The lines in the right plot represent the interpolated demand from the right panel. The equilibrium reached through a price pair (λ^{0*}, λ^{1*}) of ($y = 0.43, x = 0.3$) is the best solution that can be achieved (from blue & purple lines in left and right figure respectively). It corresponds to the lowest possible average price and to the highest possible demand for insurance.

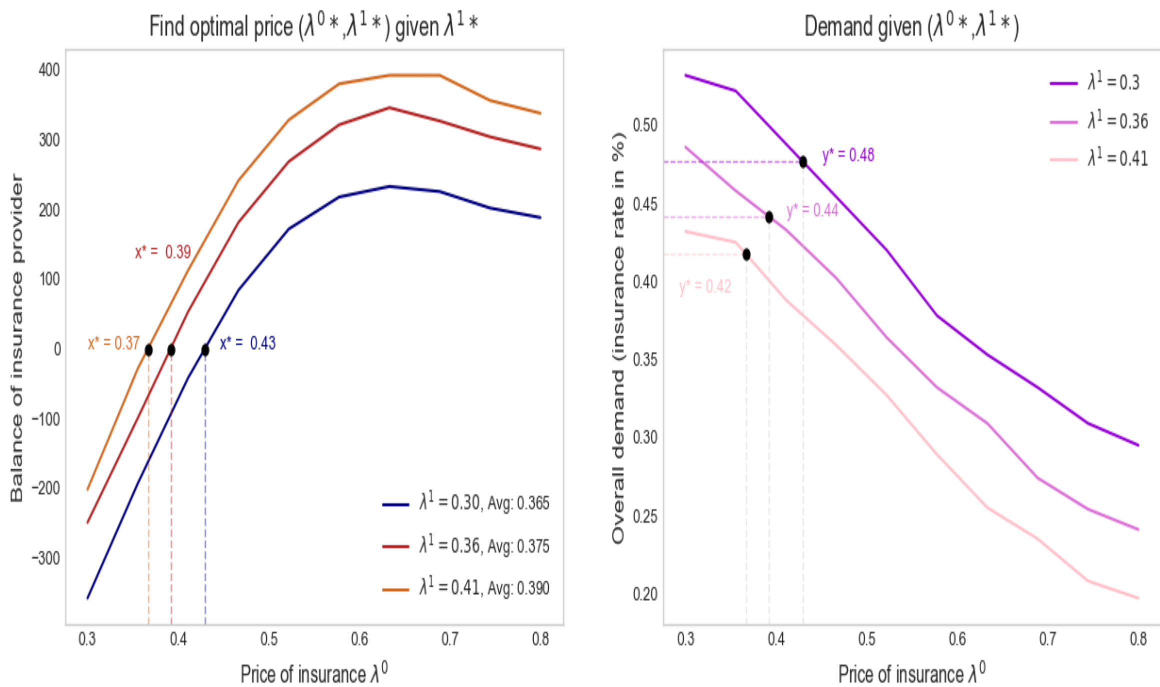


Figure 6: Equilibrium selection under perfect competition

Under the given parameter range, enforcing a no profit condition through competition in the health insurance market would lead to premium reductions of 39% for high-risk types and 36% for low-risk types. Most importantly, insurance coverage increases from 22% to 48%. But because that equilibrium is located on the lower end of the parameter range for λ^1 (for low-risk types), it cannot be ruled out that a pair $(y > 0.43, x < 0.3)$ exists which gives a higher overall insurance rate at a profit of zero[18]. However, the corner solution does not affect the general conclusion that both types profit from increased competition.

[18]Especially because figure 5 showed that demand of low-risks reacts stronger to changes in prices.

Combining a ban on price discrimination with perfect competition reduces the premiums to ($y = 0.38, x = 0.38$) according to figure 5. As seen before, such a proposal would be welcomed by high-risk types but unpopular among low-risk types.

Table 1: Equilibrium collection table

a) Discrimination allowed

Competition	($y = \lambda^{0*}$, $x = \lambda^{1*}$)
Monopoly	(0.63, 0.47)
Perfect	(0.43, 0.3)

b) Discrimination banned

Competition	($y = \lambda^{0*}$, $x = \lambda^{1*}$)
Monopoly	(0.52, 0.52)
Perfect	(0.38, 0.38)

4.2 The ACA-reform: Introducing a tax penalty $\chi > 0$

So far, it was established that supply of health insurance leads to relatively high prices for both types and low insurance rates in both groups. Among the key features of the Affordable Care Act (ACA) was a tax penalty on the uninsured, which basically is a purchase mandate. There is no long-term data available because the purchase mandate was repelled just one year after it was properly implemented. However, following Blumberg et al. (2013), Buettgens et al. (2010), Fiedler (2018) and estimations by the US Central Budget Office CBO (2017), the studies and simulations that do exist seem to find that the mandate was able or would have been able to increase insurance coverage. Especially, Blumberg et al. (2016) and Eibner & Saltzman (2015) provide empirical evidence that the mandate increased enrolment of young adults and thus could have provided an effective way to counter adverse selection.

In this section, a similar tax penalty $\chi > 0$ will be applied to all agents that can technically afford to pay the premium but chose to opt out. One would expect that the mandate increases insurance rates for both types and especially among low-risk types. A mandate $\chi > 0$ makes buying insurance more attractive because insurance provides a benefit in the future while money paid to the penalty is simply lost.[19]. A higher overall insurance rate with more low-risk types could also mean, that prices needed to sustain a balanced budget (zero profits) could be reduced. As before, the section starts with monopoly competition as in 4.1.1 and later evaluates the same two supply side interventions as in 4.1.2 and 4.1.3.

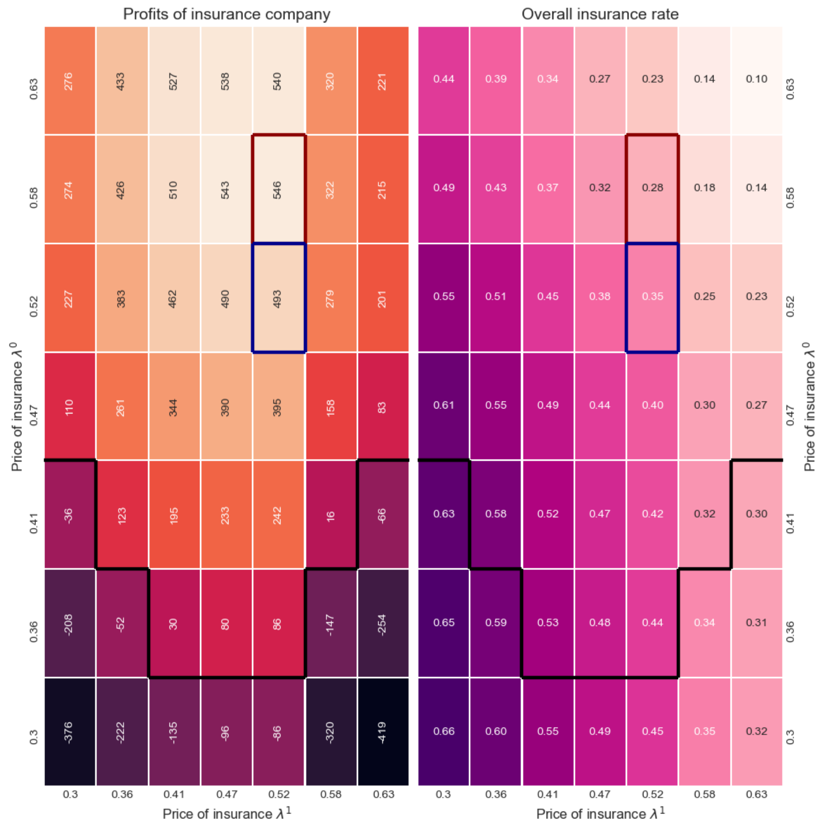
4.2.1 Monopoly insurance provision after the ACA reform

Figure 7 on the next page reports the resulting profit and demand matrices for the reformed model and allows for a direct comparison with the results from the benchmark in section 4.1.1[20]. The only difference compared to results from figure 2 is the penalty of 10% of income on agents that willingly decide not to purchase insurance. The profit maximising optimal price pair (λ^{0*}, λ^{1*}) after the reform is (0.58, 0.52) compared to (0.63, 0.47) without the penalty (both marked as red in figures 8 and 2). The monopolist's profit of 546 is significantly higher than the benchmark profit of 416. While low-risk agents pay more for insurance after the reform, high-risk agents end up paying less. As expected, demand for insurance is strictly higher in figure 7 compared to figure 2 for any given price pair. Thus, the post-reform insurance rate of 28% is higher than before but the difference of 6% points is relatively small.

[19]As the insurance trade-off for low-risk agents was worse, making the opt-out option less attractive is expected to affect this group even more than the high-risk group.

[20]In order to reduce computational time, the calculations of the new results were restricted to a matrix of 7x7 rather than the 10x10 in the benchmark model because all price combination higher than the peak are strictly dominated and can thus be disregarded.

Figure 7: Profit matrix with tax penalty of $\chi = 0.1$



Red square marks equilibrium for monopoly competition in 4.2.1, blue square marks no discrimination equilibrium in 4.2.2 and black line marks zero profit line in 4.2.3.

It can be concluded from table 2 below that the purchase mandate successfully increases coverage rates because more households opt into insurance. However, the mandate as an individual policy tool does not reduce insurance prices for all types under monopoly competition and favours high-risk individuals. The reform fails to increase the overall share of low-risk types in the overall portfolio at the new equilibrium (column 6). The positive demand effect from the penalty on low-risk agents is out-weighted by an even stronger demand effect on high-risk types (from penalty **and** lower prices). When comparing rows 1 and 2 in table 2, the within group demand increases by 12 percentage points for high-risk (21 to 33% in column 5) and 3 for low-risk agents due to the mandate (22 to 25%). Note that demand increases by 13% even if the price was raised by 8% for the low-risk group.

Table 2: Was the purchase mandate successful?

Equilibrium pair ($y = \lambda^{0*}$, $x = \lambda^{1*}$)	Count insured	Count insured low-risk	Count insured high-risk	**Within group demand** in % (high, low)	Portfolio share in % (high, low)
Pre-ACA (0.63, 0.48)	2,187	692 of 3,316	1,495 of 6,684	(21, 22)	(32, **68**)
Post-ACA (0.58, 0.52)	2,785	1,091 of 3,316	1,694 of 6,684	(33, 25)	(39, **61**)
Pre-ACA (0.58, 0.52)	2,158	1,047 of 3,316	1,111 of 6,684	(32, 17)	(49, **51**)

Scenario notes: Pre-ACA (0.63, 0.48) refers to the actual equilibrium with $\chi = 0$ and monopoly competition, red squares in fig. 2 and fig. 3 for column 5. Post-ACA introduces $\chi = 0.1$ as in the current section, red squares fig. 7 and 14 for column 5. Compared to row 1, it reports the observed change from pre-mandate equilibrium to the new equilibrium. Compared to row 2, Pre-ACA (0.58, 0.52) gives the counterfactual (grey fields in fig. 3 for column 5). In other words, the situation if the post-mandate equilibrium could be sustained in the benchmark case.

To control for the demand effect caused by the change prices, row 3 reports the counterfactual equilibrium. If (0.58, 0.52) could be sustained as an equilibrium without the mandate, demand among low-risk types would be only 17% and the low-vs-high risk ratio in the portfolio would be only 51%. Comparing rows 2 and 3 shows the ”direct” effect of the mandate. Demand implicitly increases by 8 percentage points for low-risk types (17 to 25%) but only one point for high-risk types. Consequently, the mandate enables an equilibrium with lower prices for high-risk types. To compensate, prices for the low-risk group can be increased as the purchase mandate prevents some low-risk agents from opting out compared to the counterfactual.

4.2.2 The effect of eliminating price discrimination given $\chi > 0$

If price discrimination is eliminated as part of the reform, the matrices in figure 7 would be reduced to its diagonals. The profit maximising price without discrimination would be at $\lambda^0 = \lambda^1 = 0.52$ and demand would be at 35% (marked as blue squares). This equilibrium price is the same found by banning price discrimination without the penalty in 4.1.2. However, this could be due to the relatively big steps in the grid for prices. Using a finer grid could lead to a slight reduction in the no-discrimination price somewhere between 0.47 and 0.52. While combining a ban on price discrimination with the penalty does not lead to reduced premiums, it increases the number of households that enjoy insurance coverage from 26% to 35%.

4.2.3 The effect of perfect competition on equilibrium prices given $\chi > 0$

In a monopoly, the mandate achieves the goal of raising insurance rates but fails to lead to large reductions in premiums for both groups. As previously seen, opening the market to competition drove prices down in the benchmark case. Repeating the analysis from 4.1.3 but with $\chi > 0$ confirms a similar trend which is reported in figure 8. The pair (λ^{0*}, λ^{1*}) of ($y = 0.425, x = 0.3$) gives a lower average price and a higher overall insurance rate as the benchmark model under perfect competition.

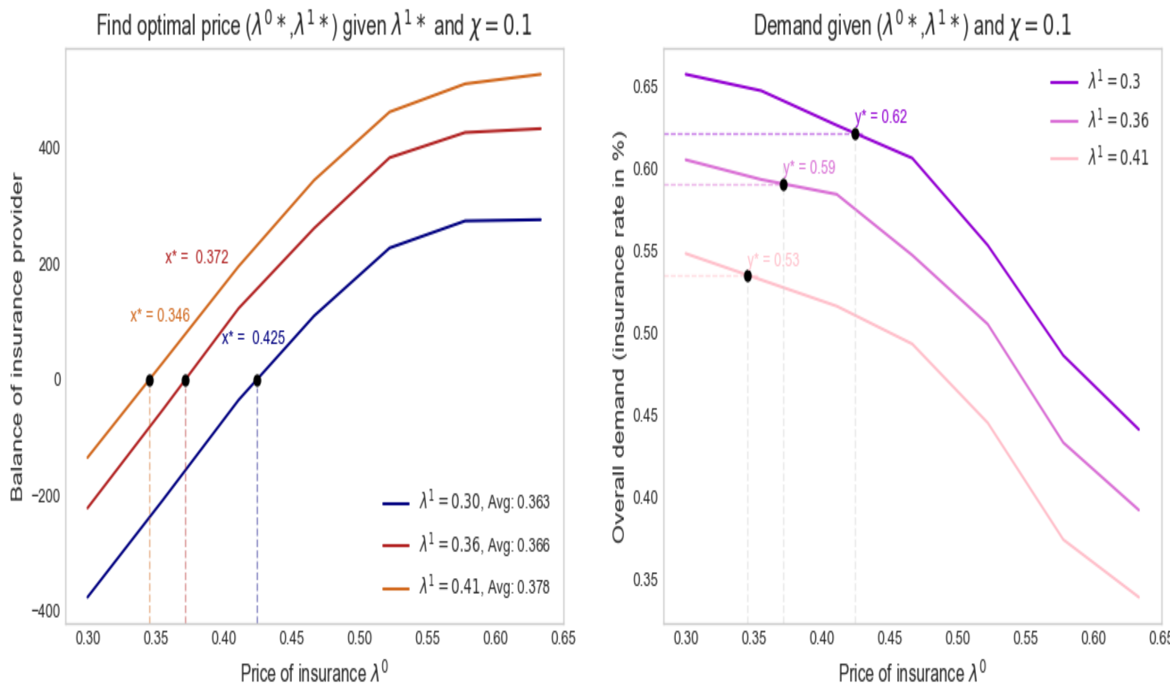


Figure 8: Equilibrium selection under post-ACA perfect competition

As expected, demand increases and premiums under perfect competition can be reduced. The mandate raised demand by 12 percentage points from previously 48% (see figure 6) to over 60%. However, the reduction in price for the high-risk types (from 0.43 in figure 6 to 0.425) is only marginal and non-existent for low-risk types. It was expected that zero profits can be achieved with lower prices if the purchase mandate applies. However and as before, the equilibrium for low-risk types at 0.3 is still a corner solution (on the lowest end of the parameter range for λ^1). While the results indicate that prices necessary to obtain zero profits are slightly lower with the mandate (at least for λ^0), the specified parameter range is not sufficient to compare the perfect competition scenarios with vs. without $\chi > 0$. Table 3 summarises all found equilibria.

	$\chi = 0$		$\chi > 0$ (ACA)	
Competition	Discrimination	No discrimination	Discrimination	No discrimination
Monopoly	$(0.63, 0.47)$	$(0.52, 0.52)$	$(0.58, 0.52)$	$(0.52, 0.52)$
Perfect	$(0.43, 0.3)$	$(0.38, 0.38)$	$(0.425, 0.3)$	not considered

Table 3: Equilibrium collection table ($y = \lambda^{0*}$, $x = \lambda^{1*}$)

4.3 From private to public: A single-payer system

Many countries run public and heavily regulated health systems with universal health insurance[21]. In its simplest form, a public single-payer system implies that taxes on income τ pay for universal insurance[22]. This section investigates if a switch from private provision to a tax funded system would be favoured by a majority in a simple vote. To be accepted, the proposal requires more than 50% of the votes in a society consisting of 6,684 low-risk and 3,316 high-risk voters[23]. It is assumed that all agents are aware of all equilibria found in the previous sections and that they make voting decisions by simply comparing the premium that would apply to them. The government's problem is to find the tax that leads to a balanced budget. Revenue is simply $10,000 * y * \tau$ and expected costs only depend on the number of people N, the share of types in the

[21] E.g., public health insurance is mandatory by law in Germany (Sozialgesetzbuch (SGB) Fünftes Buch (V)). Simply speaking, the government sets premiums (deductions from employees' wages) by law. Premiums are adjusted to secure financial stability if the insurance system makes losses or profits.

[22] In contrast to a classic setting where taxes on income would affect labour supply, agents in this model are assumed to work all the time and labour supply, wage dynamics or frictions are not modelled.

[23] Numbers are from simulation with N = 10,000 and share of low-risk types of 0.66.

population $Pr(\theta)$ and the expected claims for each type $y(1 - mean(\zeta^{\theta}_{t+1}))$.

$$U^{gov} = \min_{\tau} |R\Big(\tau, y\Big) - C\Big(Pr(\theta = 0), Pr(\theta = 1)\Big)| \tag{14}$$

Figure 4.3 reports the resulting linear relationship with an equilibrium tax at $\tau = 0.33$[24]. Whether a public system is preferable again depends on the perspective.

A comparison of $\tau = \lambda^{public} = 0.33$ with row 1 of table 3 shows that the proposal would be accepted with 100% of votes as both types are better off in the public system. If perfect competition is possible (row 2), low-risk agents prefer a discriminating plan of $(0.43, 0.3)$. Thus, the proposal would fail with only 33% of votes.

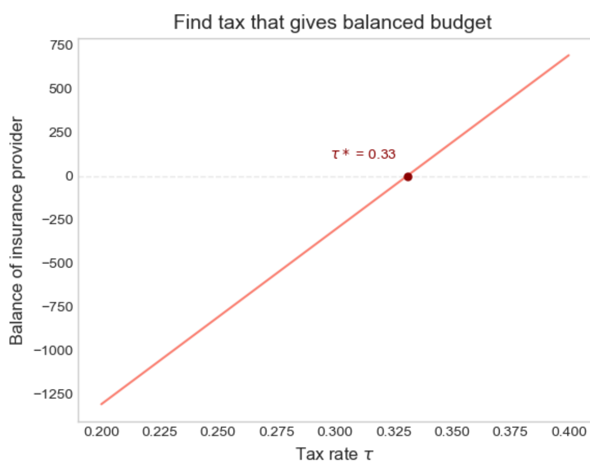


Figure 9: Optimal tax on income

It can therefore be concluded that political support for a system switch in this simple model depends on which alternative regulatory options are feasible.

[24]The weighted average financial burden from $(0.33 * 0.43 + 0.66 * 0.3) = 0.34$, is very close to the tax on income necessary to sustain universal coverage. Mandating a 100% insurance rate neither increases nor decrease the average cost of insurance.

5 Robustness and Discussion

As indicated in footnote 16, the type-specific demand matrices in figure 3 can show some irregularities where demand seems to change slightly for one type θ even though λ^θ was kept constant and only the price of the other group was changed. This can be explained by different convergence speed when solving and simulating the 100 individual runs[25]. As a robustness check, the whole analysis was redone with a fixed number of 70 solution and 20 simulation iterations. This way, all fields in the 10x10 result matrices are generated by a more comparable data generating process. The results can be found in appendix F. Using an equal number of iterations cured the fluctuations without affecting the overall conclusion (equilibrium profits only change marginally from 416 to 406 at the peak). The robustness check also allows for a graphical view on household consumption without noise, which can be used to assess the plausibility of the observed consumption behaviour. Figure 10 reports average consumption of the insured households in the blue panels 1 and 3 (high-risk on the left and low-risk on the right). By the same logic, the orange-coloured panels 2 and 4 report consumption of the uninsured. Starting with the blue panels for insured agents, consumption is highest for both groups at the bottom left corner and declines with rising prices either vertically or horizontally. Within the group of insurance takers, low-risk agents (see panel 3) would enjoy higher consumption at all discussed equilibrium candidates. When comparing within the group of high-risk agents (panels 1 and 2), insured high-risk agents consume slightly more for low values of λ^0. For high values of λ^θ, demand converges to 0. Average consumption converges to 0.5 for high-risk types in panel 2 and to 0.75 for low-risk agents in panel 4, implying

[25]Especially the stopping rule for simulating the data is a concern as described in appendix C.

that the average uninsured agent does not save[26]. While insurance provides higher disposable income for high-risk agents compared to taking the health shock lottery, insurance never gives a higher income than the health shock lottery for low-risk types (panels 3 and 4). Nevertheless, insurance rates for low-risk types were larger than zero for most price pairs throughout this study (see for example figure 3).

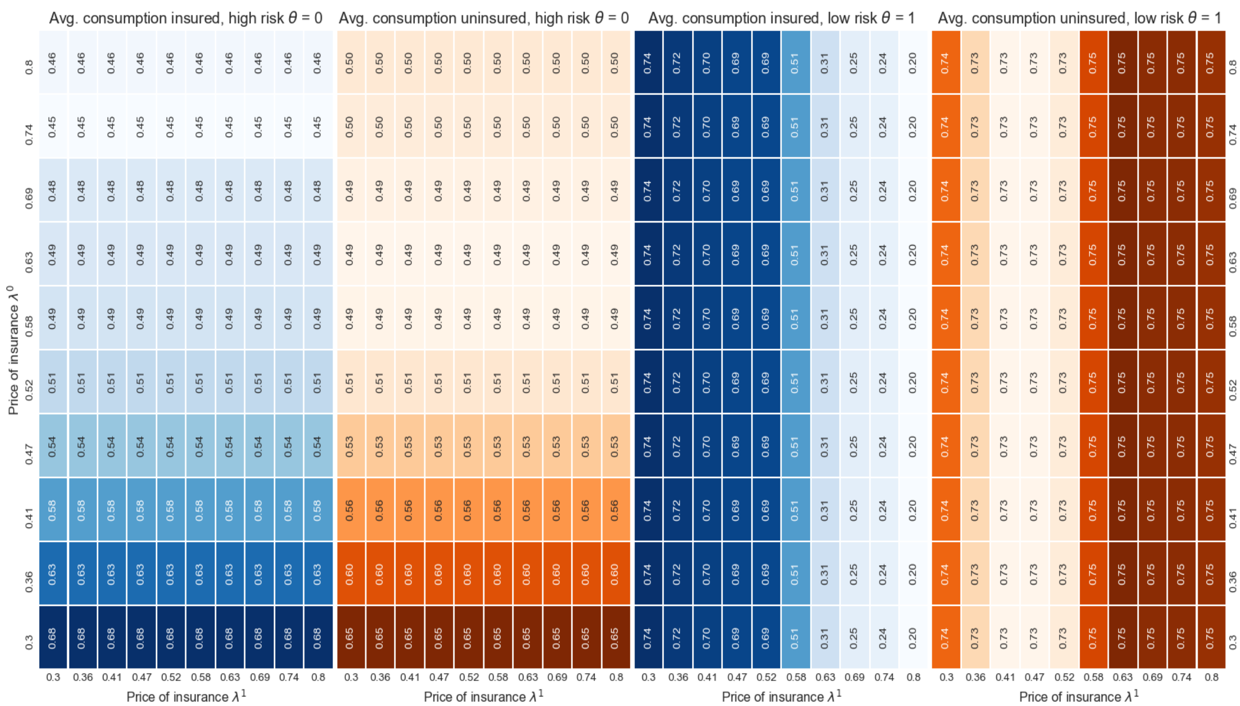


Figure 10: Type and insurance choice-specific consumption

The design of the choice probabilities allows agents to behave mathematically "irrational" (see page 20 and appendix page 55 for details). This relaxation leads to more realistic behaviour as factors other than just the two modelled in this paper (m & θ) affect insurance choices in reality.

[26]Recall that the simulation stopped when the distribution of m is stable and a consequence of that is that agents consume all disposable income ($y * mean(\zeta^{\theta})$).

Limitations and potential extensions

While the model is supposed to represent the US health system, its applicability suffers from some critical simplifications. Concerning the firm's optimisation problem, additional choice variables other than the premium, such as deductibles and co-payments, are neglected. With respect to the household problem, labour supply would be an immediate factor of interest in a model allowing for other forms of insurance provision (as studied by French et al. (2016)). Additionally, the savings decision would be more realistic if households had an alternative investment option for money they spend on buying insurance (as proposed by Asmussen et al. (2013)). The sum of these limitations makes it difficult if not impossible to generalise the results and the model's predictive power for US market dynamics is limited. The most obvious extension would be to incorporate Medicare, Medicaid and employers as other potential forms of health insurance provision into the model.

According to Keane et al. (2011), structural models can be validated by matching the model with empirical data and to accept or reject its fit based on some statistical tests. Alternatively, the authors suggest to evaluate the predictive power of a model through in- or out-of-sample tests[27]. In general, validating the model from this thesis without excess to micro-level data on e.g., insurance status, premiums, medical expenses, and a risk-type indicator is not possible. Thus, matching the findings with empirical data is another obvious extension to this project.

[27] Another common approach is the so-called Method of Simulated Moments (MSM), an estimator which minimises the difference between the real moments in the data and the corresponding moments generated from the model. In other words, the estimated parameters are chosen such that model results are as close to the data as possible. Due to scope considerations, no MSM was implement specifically for this model but for reference, consult McFadden (1989).

6 Conclusion

The objective of this thesis was to study price dynamics in a model for health insurance where optimal reactions of households are taken into account when optimising the price. The data generated with the proposed approach was used to identify equilibrium price candidates for a number of scenarios. As one of the discussed interventions, the ACA mandate achieved its purpose of mitigating adverse selection by increasing insurance rates by 6 and 12 percentage points under monopoly and perfect competition respectively. In principle, it is not surprising that a purchase mandate increases the demand for a product or that higher prices reduce demand. The main contribution of the presented approach is that the magnitude of changes to the system can be quantified, which is key for performing quantitative policy analysis. For the considered range of parameters, all consumers profit from increased competition, which reduces prices by over a third. Preventing the insurance provider from discriminating by risk type leads to a reduction of prices for high-risk household of around 17% at the cost of low-risk households. Finally, the success of a policy proposal to switch from private provision to a tax funded system would depend on what regulatory alternatives are feasible.

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A Appendix

Appendix A: Parameterisation

Model parameters

Table 4 summarises what parameters were pre-defined, with what value they were initialised as well as their purpose in the model. When looking at equation (2), $\beta = 1$ would imply that the future is valued equally as much as today. A $\beta < 1$ discounts the future value making the agent impatient to some degree. The indicated values for λ^0 and λ^1 were used to generate the illustrative value of choice functions from section 3.1. For the main results of this paper presented in section 4, these two variables will be dropped from the list of exogenous parameters and treated as endogenous variables of choice. Note that the tax penalty χ is indicated as *0* but will be set to $\chi > 0$ when re-running the model with post-ACA specification in section 4.2.

Table 4: Parameter table for solution method

Parameter	Value	Description
ρ^0	0.5	risk aversion for high-risk types
ρ^1	0.4	risk aversion for low-risk types
β	0.96	discount factor
R	1.04	interest rate
y	1	fixed income per period
σ_ϵ	0.2	variance of taste shock / smoothing parameter
χ	0	tax penalty for no insurance
O	0	operating costs for insurer
λ^0	0.4	exogenous price of insurance
λ^1	0.3	exogenous price of insurance
m_{min}	$1e^{-6}$	minimum value in $\mathcal{G}_m$
m_{max}	10	maximum value in $\mathcal{G}_m$
Nm	100	number of points $\mathcal{G}_m$
Neps	8	number of numerical integration nodes
max_iter_solve	5000	maximum number of iterations
solve_tol	$1e^{-1}$	tolerance for solving

Simulation parameters

Table 5: Parameter table for simulation method

Parameter	Value	Description
$simT$	400	max number of iterations
$simN$	10.000	number of agents simulated
$Pr(\theta = 0)$	0.33	share of high-risk types in %
$Pr(\theta = 1)$	0.66	share of low-risk types in %
$m^{initial}$	1e-1	starting value of m
simulate_tol	50	tolerance for simulating

The higher share of low-risk types is in line with data showing that only a small share of the US population accounts for nearly half of the medical expenses, see Peterson-KFF (2021). While $m^{initial}$ is set universally to *0.1*, random numbers between *0* and *0.1* will be added to it to create some heterogeneity across agents.

Appendix B: Simulation method and logsum taste shocks

This section presents the numerical simulation algorithm described in section 3.2.

Algorithm 3: The *simulation* method

Input: V and C from VFI, $(\lambda^0, \lambda^1), (\omega_{k^{\zeta^0}}, \omega_{k^{\zeta^1}})$, $(\mathcal{G}_{\zeta^0}, \mathcal{G}_{\zeta^1})$, m$^{initial}, T_{max}, tol$

Output: (TxN) matrix for c, m, and z

1 Simulate shocks by drawing matrix of indexes with shape (TxN). Each index gets drawn with probability equal to the weights vector $\omega_{k^{\zeta^\theta}}$;

2 Fill shock matrix by assigning the value from $\mathcal{G}_{\zeta^\theta}$ which corresponds to the index matrix. $\zeta^\theta = \mathcal{G}_{\zeta^\theta}[shock\_index]$;

3 Generate matrix of random numbers, the time fixed state variable θ_i and initialise starting values for m through $m^{initial}$;

4 **for** *each individual* n *in each period* t *in* $1:T$ **do**

5   # if insurance is not affordable (if premium > sim.m[t,n]);

6   C0 = $interp\_1d(\mathcal{G}_m, V[0, \theta, :], m[t, i])$;

7   set sim.c[t,n] = C0 & sim.z[t,n] = 0;

8   # if insurance is affordable;

9   **for** z *in* Z **do**

10         $v_{i,t}^{interpolated}[z] = interp\_1d(\mathcal{G}_m, V[z, \theta, :], m[t, i])$;

11         $c_{i,t}^{interpolated}[z] = interp\_1d(\mathcal{G}_m, C[z, \theta, :], m[t, i])$;

12   **end**

13   Probability of choice: $prob = logsum(v_{i,t}^{interpolated}[0], v_{i,t}^{interpolated}[1], \sigma_{eta})$;

14   # compare *prob* and random number from step 3.;

15   **if** $rand > prob$ **then**

16         $c_{i,t} = c_{i,t}^{interpolated}[z = 0]$# decision against insurance;

17   **else**

18         $c_{i,t} = c_{i,t}^{interpolated}[z = 1]$# decision for insurance;

19   **end**

20   # update next period's starting values given decision in t;

21   **if** $t < T - 1$ **then**

22         $a_{t,n} = get\_a(c_{t,n}, m_{n,t}, z_{n,t}, \theta)$;

23         $p_{t+1,n} = \Big(Y\zeta_{n,t}^1\theta + Y\zeta_{n,t}^0(1-\theta)\Big)(1 - z_{n,t}) + Y(z_{n,t})$;

24         $m_{t+1,n} = R(a_{n,t}) + p_{t+1,n}$;

25   where ζ^θ are the (T, N) shock matrices for $\theta \in (0, 1)$ from step 2

26   Stop if [difference in distribution of $m_{t+1,n}$ and $m_{t,n}$] $< tol$

27 **end**

The extreme type 1 distributed taste shocks have a closed for solution known as the *logsum* function (line 13 and equation 8 in model section). For a detailed discussion the reader is referred to Iskhakov et al. (2015). The variance σ_ϵ acts as a smoothing factor and as a consequence, agents do not strictly select the mathematically optimal choice.

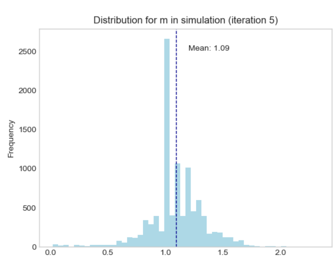
Listing 1: Effect of σ_ϵ

```
V_plus , prob = logsum(A,B,sigma_eta) # basic logsum function
# call with similar values A = 2, B = 2.1 and sigma = 0.2
V_plus , prob = logsum(2,2.1,0.2)
2.195 , array([0.378, 0.622])
# call with high sigma
V_plus , prob = logsum(2,2.1,0.9)
2.675 , array([0.472, 0.528])
```

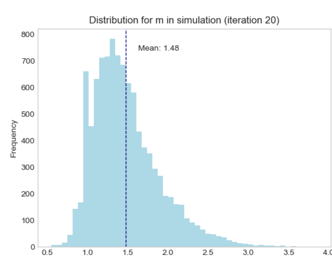
From the example above, one can see that when comparing the option A = 2 and option B = 2.1, a variance of 0.2 results in choice probabilities of 0.38% for option A and 0.62% for option B. If the variance is increased to 0.9, the agents would be more indifferent between the two and only select the mathematically preferred option B 53% of the time. So the higher the variance, the larger the difference between the compared values has to be for agents to have a strict preference over the two choices.

Appendix C: Simulation stopping criterion

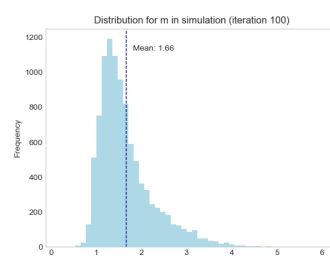
The idea here is to stop the simulation as soon as the simulation in m is considered to be ”stable”. This is implemented by calculating two histograms at the end of each iteration t, comparing the distribution of m_{t-1} with the post-decision distribution of m_t. The histograms are designed to have a number of pre-defined fixed bins to make sure that the same value ranges are compared[28]. The difference is calculated for each bin individually and the simulation is stopped as soon as the maximum difference over all bins is less than 50. This implies that the distribution is considered ”stable” if less than 50 out of 10.000 agents experience a change in m that let’s them travel to a different bin (which corresponds to 0.5% of agents). The chosen tolerance does not account for changes in m outside of the specified range of the histogram. However, it achieves the underlying goal of stopping when the distributions are relatively close to each other.



a) 5 iterations



b) 20 iterations



c) 100 iterations

The figure illustrates the distributions of m after 5, 20 and 100 iterations. It becomes clear that the distributions in b) and c) are more similar but the right tail grows with the number of iterations. If the tail grows slowly enough, the stopping criterion might still be triggered even if the distribution is still changing.

[28]Specifically values for m between 0 and including 5 are considered with a fixed number of 50 bins.

Appendix D: Type-specific demand after ACA reform

Table 14 reports the type-specific demand after a tax of 10% on income was introduced as a penalty. This allows for a direct comparison to figure 3.

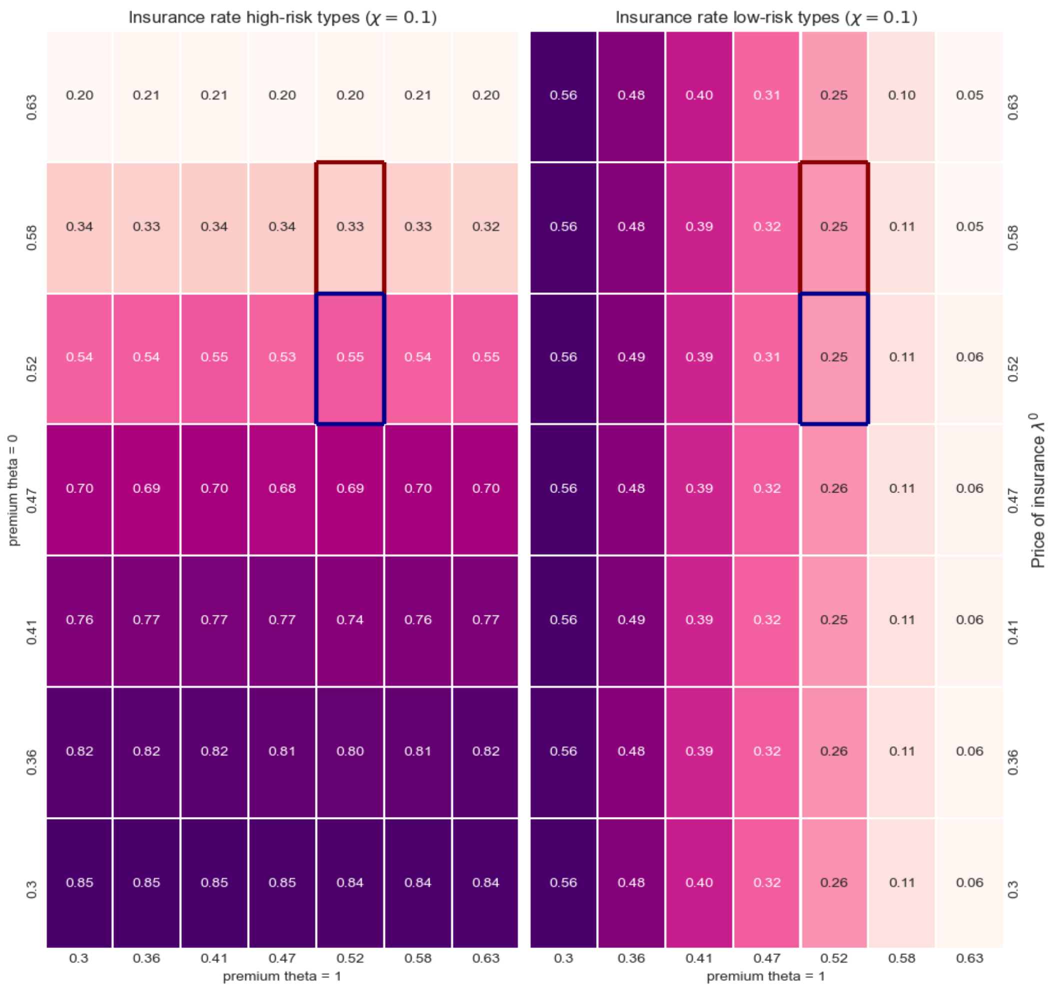


Figure 14: Demand for insurance by type given $\chi = 0.1$

(To go back to table 2 (page 36), click here.)

Appendix F: Robustness check of profit matrix

Fixing the number of iterations as discussed in section 5 allows for a direct comparison to figure 2.

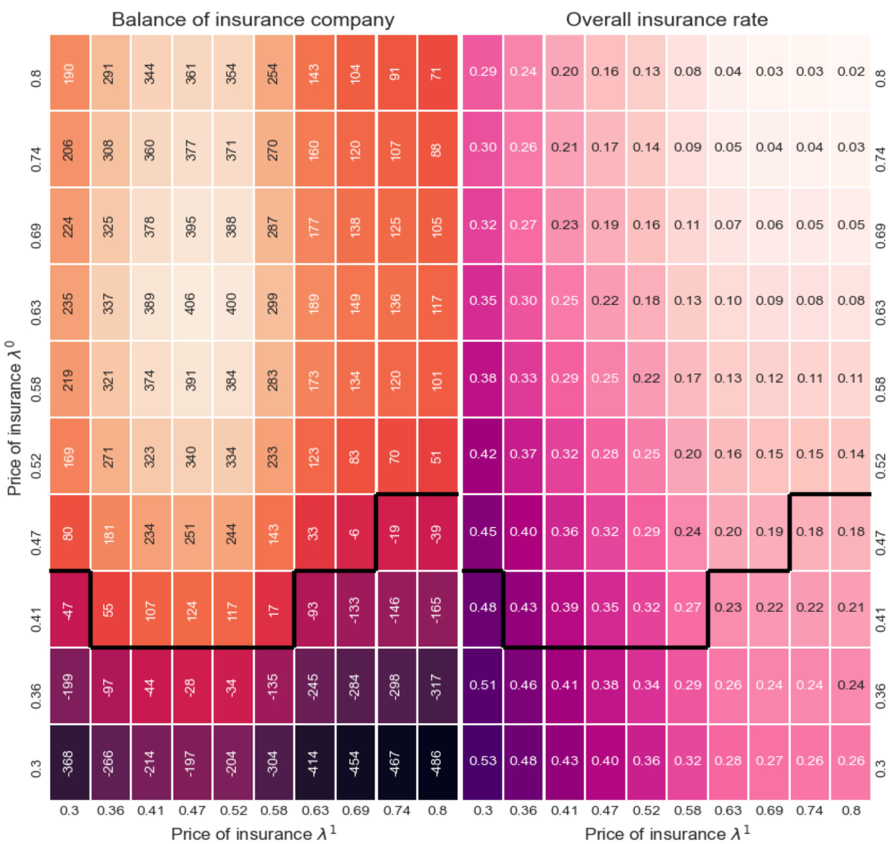


Figure 15: Profit matrix generated with 70 solving and 20 simulation iterations

Fixing the number of iterations as discussed in section 5 also allows for a direct comparison to figure 3.

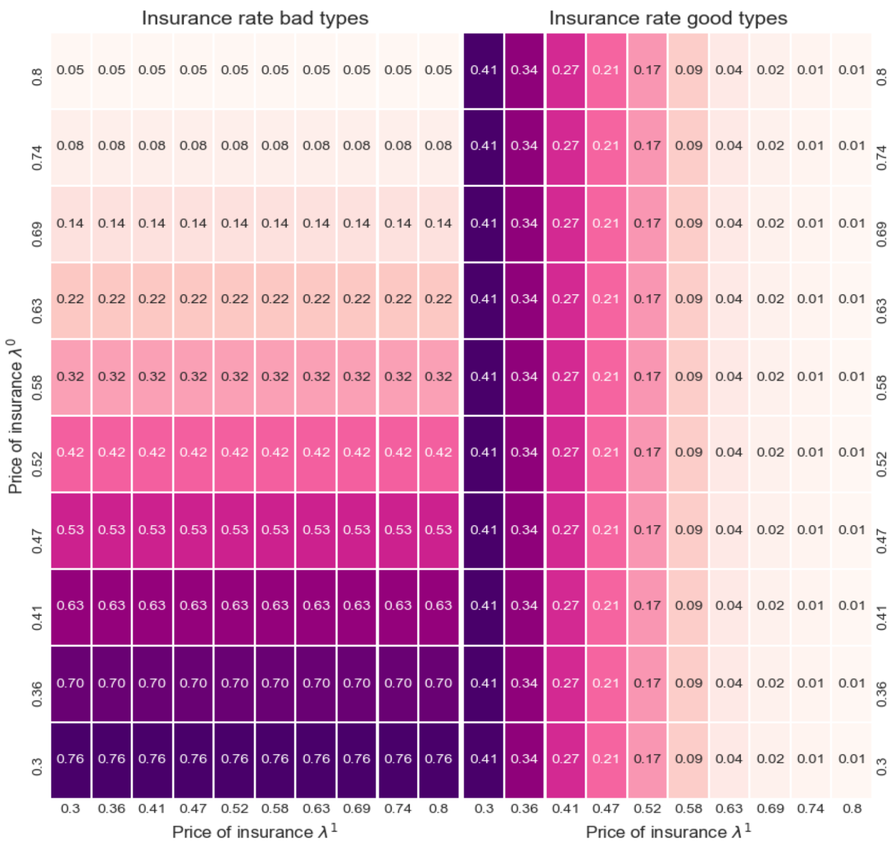


Figure 16: Type-specific demand generated with 70 solving and 20 simulation iterations