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Three Essays in Health Economics

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Getafe, Mayo 2017

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Acknowledgements

I would like to express my deepest gratitude to Matilde Machado for being the best advisor I can imagine. I would also like to acknowledge the work of my thesis committee members, Julio Cáceres-Delpiano and Luigi Minale, and I would like to thank the other faculty members of the Universidad Carlos III de Madrid who have helped me at various stages of my research career: Jesús Carro, Luis Corchón, Ángel Hernando-Veciana, Natalia Fabra, Félix Lobo, Jaime Millán-Quijano, Ricardo Mora, Diego Moreno, Gabriel Smagghue, and Jan Stuhler. Finally, I would like to thank Roger Feldman, Pau Olivella, and Ulrich Wagner for writing my reference letters, and Gerard van den Berg and Kathleen Nosal for hosting me during my stay at the University of Mannheim.

My colleagues and friends can, of course, not go unnoticed. Thanks to: Emre Ergemen, Federico Masera, Andrés García-Suaza, Meng Li, Salvatore Lo Bello, Mehdi Hamidi Sahneh, Christos Mavridis, Tilak Mukherjee, José Carbó Martínez, Federico Curci, Michele Rosenberg, Victor Troster, Anil Yildizparlak, Marco Serena, Nora Wegner, Lovleen Kushwah, Fabian Rinnen, Albrecht Bohne, Jean-François Mercier, Maximilian Nowroth, Martin Krüger, Michaela Brützel, Caroline Harmuth, Jarek Brostowicz, Frieso Pennekamp, Matthias Meier, and Stephan Adams.

Last but not least, I would like to thank Liliane Marcos dos Santos and my parents for their unconditional support. I dedicate this thesis to the memory of my grandmothers, Magdalene Panthöfer and Erika Kämpfer.

Abstract

Expenditures for health care and health insurance have increased rapidly over the last several decades. This thesis is composed of three essays that analyze markets for health care and health insurance, respectively.

Chapter 1 studies risk selection between public and private health insurance when some, but not all, individuals can opt out of otherwise mandatory public insurance. Using a theoretical model, I show that public insurance is adversely selected when insurers and insureds are symmetrically informed about health-related risks, and that there can be adverse or advantageous selection when insureds are privately informed. Using data from the German Socio-Economic Panel, I find that: (1) public insurance is, on balance, adversely selected under the German public health insurance with opt-out scheme, (2) individuals advantageously select public insurance based on risk aversion and residential location, and (3) there is suggestive evidence of asymmetric information in the market for private health insurance.

Chapter 2 investigates whether doctors prescribe antibiotics to protect themselves against potential malpractice claims. Using data from the National Ambulatory Medical Care Survey on more than half a million outpatient visits between 1993 and 2011, I find that doctors are 6% less likely to prescribe antibiotics after the introduction of a cap on noneconomic damages. Over 140 million discharge records from the Nationwide Inpatient Sample do not reveal a corresponding change in hospital stays for conditions that can potentially be avoided through antibiotic use in the outpatient setting. These findings, as well as a stylized model of antibiotic prescribing under the threat of malpractice, suggest that liability-reducing tort reforms can decrease the amount of antibiotics that are inappropriately prescribed for defensive reasons.

Chapter 3 tests whether tort reforms induce physicians to adjust the amount of time spent with patients. Analyzing data from the National Ambulatory Medical Care Survey on more than half a million physician office visits between 1993 and 2011, I find that three of the most common tort reforms – caps on noneconomic damages, caps on punitive damages, and reforms of the joint-and-several liability rule – have no impact on length of ambulatory care visits. I discuss potential explanations for this finding.

Contents

List of Figures

List of Tables

1 Risk Selection under Public Health Insurance with Opt-out

1.1 Introduction

Both mandatory public health insurance and freely competitive markets for private health insurance have their disadvantages. Public health insurance typically does not leave much room for consumer choice and often involves a one-size-fits-all policy. Facing inadequate coverage in public insurance, many individuals turn to private insurers and end up holding two health insurance policies.[1] With a freely competitive market for private health insurance, on the other hand, there may be too little pooling of risks and insufficient access to health insurance from a social point of view. Access to health insurance can become severely limited in the presence of asymmetric information, which may manifest itself in contracts with too little coverage (Rothschild and Stiglitz 1976) or in a complete break down of some segments of the insurance market (Akerlof 1970, Hendren 2013).

Parallel public and private health insurance systems can overcome these drawbacks to some extent. However, whenever private insurers compete with a public option, there is the concern that the former are able to cream skim the best risks, leaving the public option adversely selected. In this paper, I study risk selection between public and private health insurance in Germany. The German health insurance system is an interesting case to consider as it allows only a part of the population to choose between public and private insurance, where those who choose private insurance do not contribute towards financing the public plan. This system, which I will refer to as public health insurance with opt-out, guarantees a certain degree of risk pooling in public insurance, at the expense of restricting the choice of some individuals.[2]

I begin the analysis by constructing a theoretical model in which a single public plan that is financed by risk-unrelated contributions coexists along with a market for private health insurance in which insurers compete à la Rothschild and Stiglitz (1976). The purpose of the model is twofold. First, it shows that private insurers are not always able to cream skim the best risks out of the pool of individuals who can choose to become privately insured, even though private insurers have full flexibility in tailoring their contracts to attract good risks. Instead, the model predicts that selection depends on the informational scenario. Under symmetric information, selection against the public plan is adverse: those who are eligible to opt out and high risk stay in public insurance, because they profit from the implicit subsidies they

[1] For example, 44.9% of Australians, 15.6% of Italians, and 10% of the British hold private health insurance, although all of these countries provide universal healthcare (Colombo and Tapay 2004). Many of these private policies are duplicative, i.e., they include services which are already covered by universal insurance.

[2] While peculiar, Germany is not the only country with such a health insurance system; Argentina, Chile, Colombia, and Peru have similar arrangements.

receive from pooling with those who cannot opt out, while those who are eligible to opt out and low risk buy private insurance. Under asymmetric information, there can be adverse or advantageous selection into public insurance. The public plan can be advantageously selected because private insurers offer contracts with varying degrees of coverage in order to screen different risk types. This can lead to a situation in which relatively healthy individuals, who are offered a contract with little coverage in private insurance, stay in public insurance, because they dislike the risk that comes with the private contract, whereas some relatively sick individuals, who are offered a private contract with generous coverage, choose private insurance. The second purpose of the model is that it suggests a test of asymmetric information, which differs from the *positive correlation test* of Chiappori and Salanié (2000).

Drawing on data from the German Socio-Economic Panel (SOEP), I seek to answer the following three questions empirically: What is the nature of selection between public and private health insurance? What are the sources of selection? Is there asymmetric information in the market for private health insurance?

Selection will be captured by the correlation between health insurance choice (public or private) and subsequent healthcare use. To overcome the well-known issue that this correlation can reflect both moral hazard and selection, I measure healthcare use with hospitalisations. Since several studies have shown that there is no incentive effect of private health insurance coverage on hospitalisations in Germany, we can attribute the correlation between health insurance choice and hospitalisations entirely to selection. Using 14 years of data from the SOEP, I find a negative correlation between the choice to opt out of public insurance and future hospitalisations. This correlation indicates adverse selection into public insurance, which, to some extent, is expected since private health insurance premiums are based on individual risks and public health insurance contributions are not. I then decompose selection into a part that is due to observable characteristics of insureds which affect the relative price between public and private insurance and a part that is due other factors. Results suggest that differences in the relative price between public and private insurance explain at least one-third of the adverse selection into public insurance.

To study the sources of selection, I follow Finkelstein and Poterba (2014) and search for unused observables that are correlated with both health insurance choice and healthcare use after controlling for observables, where unused observables are variables that are observed by the econometrician but which insurers do not use to calculate premiums. I find three unused observables that qualify as sources of selection: self-assessed health, risk aversion, and residential location. The former gives rise to adverse selection and the latter two give rise to advantageous selection into public insurance.

I test for asymmetric information exploiting the predictions of the theoretical model and find evidence in favour of it: the decision to opt out of public insurance is nonmonotone in self-assessed health, a scenario which can only arise under asymmetric information according to the theoretical model. However, the evidence for asymmetric information should be taken as merely suggestive, because the coefficients that reveal the nonmonotone pattern are imprecisely estimated due to a lack of statistical power.

This paper is related to several distinct literatures. The theoretical model relates closely to Olivella and Vera-Hernández (2013), who incorporate a public insurance plan into the canonical model of a competitive health insurance market due to Rothschild and Stiglitz (1976). The main difference between their model and the model presented in this paper lies in the financing of the public plan: Olivella and Vera-Hernández (2013) consider a tax-financed public plan, whereas I study a budget-balanced, contribution-financed public plan. The latter differs from the former in two important aspects. First, public insurance has a price attached to it, which does not have to be paid if an individual decides to opt out. Second, the price of public insurance is endogenously determined, by the characteristics of those who choose public insurance.

This paper moreover contributes to the literature on selection between a public option and competing private health insurance plans. One focus of this literature has been on selection between traditional fee-for-service Medicare and private Medicare Advantage plans (Brown *et al.* 2014, Newhouse *et al.* 2012, Newhouse *et al.* 2015). Recently, several empirical papers have focused on the German health insurance system. Grunow and Nuscheler (2014) study switches between public and private health insurance and find that individuals who have experienced a negative health shock exhibit an increased propensity to switch from private to public insurance. Bünnings and Tauchmann (2015) investigate the decision to opt out of public insurance and find that young and healthy individuals are disproportionately more likely to opt out. These two studies, while suggestive of adverse selection into public insurance, do not relate health insurance choice to subsequent healthcare utilization. In concurrent work, Polyakova (2014) uses a regression discontinuity design and concludes that private insurers are not successful at cream skimming the best risks, which she explains with heterogeneous tastes for convenience and the long-term nature of private health insurance contracts. The present paper offers a theoretical explanation why private insurers are not always able to cream skim the best risks.

Finally, this paper is also related to the literature on testing for asymmetric information in insurance markets, which is surveyed by Cohen and Siegelman (2010) and Einav *et al.* (2010). The paper follows Olivella and Vera-Hernández (2013) and de la Mata *et al.* (2015) in measuring healthcare use with hospitalisations when testing for asymmetric information.

The rest of this paper is organised as follows. Section 1.2 lays out the theoretical model. Section 1.3 summarises the German health insurance system. Section 1.4 describes the data. Section 1.5 explains the empirical approach. Section 1.6 reports the empirical results. Section 1.7 discusses policy implications and concludes. All proofs are delegated to the Appendix.

1.2 A Model of Public Health Insurance with Opt-out

This section introduces a model of public health insurance with opt-out. The model is geared towards the German health insurance system, which features income-dependent contributions to public insurance, a budget-balanced public plan, an opt-out policy that is based on income, and risk rating in private insurance. As in Olivella and Vera-Hernández (2013), a public insurance plan coexists along with a market for private insurance à la Rothschild and Stiglitz (1976). Individuals must choose exactly one insurance plan. The model describes the market for health insurance within a risk class, in which individuals are observationally equivalent except for the two features described below.

There is a measure one of individuals who differ along two dimensions: their probability of becoming sick and their income. There are $n \geq 2$ different risks, $0 < p_1 < \ldots < p_n < 1$, where p_i is the probability with which an illness occurs. Under symmetric information, a consumer's probability of falling sick is publicly observable, whereas it is private to the consumer under asymmetric information. In case of falling sick, individuals suffer a monetary loss, d, against which they can insure themselves. There are two levels of income, y_L and y_H, which are publicly observable and satisfy $y_H > y_L > d$. The right to opt out of public insurance is granted based on income. Individuals who earn the low income, y_L, are mandatorily insured in public insurance, while individuals who earn the high income, y_H, can stay in public insurance or opt out, buying private insurance instead.

Low-income earners play only a subordinated role since they do not choose their insurance contract. They are completely characterized by three parameters: their fraction of the population, λ_L, their income, y_L, and their average risk, p_L, where $p_1 \leq p_L \leq p_n$. High-income earners, on the other hand, make an active choice between public and private insurance. The fraction of high-income earners who is of risk p_i is denoted by λ_i, where $\lambda_i > 0$. The fraction of high-income earners in the population is given by $\sum_{i=1}^{n} \lambda_i = 1 - \lambda_L$. Henceforth, I refer to an individual with risk p_i and income y_H as a type p_i.

An insurance contract is a vector $I = (\alpha, \beta)$, where α is the insurance premium and β, $1 \geq \beta \geq 0$, is the co-insurance rate, i.e., the fraction of the damage which the insurer does not cover. Expected utility of type p_i holding insurance policy $I = (\alpha, \beta)$ is given by

$$U(I, p_i) = p_i u(y_H - \beta d - \alpha) + (1 - p_i) u(y_H - \alpha),$$

where u is strictly increasing, strictly concave, and twice continuously differentiable.

The public insurance plan, $I^{pub} = (\tau y, \eta)$, is announced at the outset and constitutes a committed offer. It consists of a contribution rate, τ, which multiplied by the income yields the insurance premium, and a co-insurance rate, η, which is the fraction of the damage that will be not be covered by public insurance. Public health insurance entails two forms of redistribution: from the rich to the poor, as premiums increase with income, and from the healthy to the sick, as premiums do not depend on risk. Public insurance is financed through the contributions of its members. To maintain a balanced budget, the government must set the contribution and co-insurance rates such that revenues equal expected cost:

$$\tau\left(\lambda_L y_L + \sum_{i=1}^{n} \lambda_i s\left(p_i\right) y_H\right) = \left(1-\eta\right) d\left(\lambda_L p_L + \sum_{i=1}^{n} \lambda_i s\left(p_i\right) p_i\right), \tag{1.1}$$

where $s(p_i)$ equals one (zero) if type p_i joins public insurance (private insurance). Note that all individuals who can choose between public and private health insurance pay the same premium for public insurance: τy_H.

After the public plan is announced, $m \geq 2$ private insurers simultaneously offer contracts. Private insurers are risk neutral, incur no administrative cost, and expect the following profit from selling the contract $I = (\alpha, \beta)$ to an individual with risk p_i:

$$\pi(I, p_i) = \alpha - p_i\left(1-\beta\right) d.$$

Observing the menu of insurance plans available to them, high-income earners maximise their expected utility by choosing between public insurance and the best private contract which is available to them. The following tie-breaking assumption is made to avoid the indeterminacy of the equilibrium strategy profile that arises in the knife-edge case in which one type is indifferent between public and private insurance.

Assumption 1. *A high-income earner who is indifferent between public insurance and the best available private insurance contract chooses public insurance.*

Equilibrium of the health insurance market is defined as follows.

Definition 1. An equilibrium is a strategy profile $s^* = [s^*(p_i)]_{i\in\{1,\ldots,n\}}$ and a set of contracts C^*, which includes the public plan, such that:

1. Every contract in C^* is selected by some consumer.
2. No contract in C^* yields negative profits.
3. There is no single contract outside of C^* that, if offered, will be selected by consumers and will generate nonnegative profits for the insurer.
4. For $i \in \{1, \ldots, n\}$: $s^*(p_i) = 1$ if $I^{pub} \in \arg\max_{I\in C^*} U(I, p_i)$, and $s^*(p_i) = 0$ otherwise.
5. The government budget is balanced: equation (1.1) holds for $s = s^*$.

The first three conditions are adapted from Rothschild and Stiglitz (1976). The fourth condition requires high-income earners to decide optimally between public and private insurance, incorporating the tie-breaking rule posited in Assumption 1. The fifth condition guarantees that the public budget is balanced in equilibrium. In light of the fact that the majority of high-income earners in Germany stay in public insurance, I consider only equilibria in which at least some high-income earners choose public insurance.

Following Einav *et al.* (2010), I say that the public plan is adversely selected if the expected cost of insuring the high-income earners who choose public insurance in equilibrium is higher than the expected cost of insuring the population of high-income earners.

Definition 2. I^{pub} is adversely selected if $\mathbb{E}_p[pd \mid s^*(p) = 1] > \mathbb{E}_p[pd]$.

Conversely, I say that there is advantageous selection into public insurance if the reverse inequality holds. Note that the low-income earners do not enter in the definition of selection. This means that there is adverse selection into public insurance if and only if private insurers are able to cream skim the best risks out of the pool of individuals who are allowed to opt out of public insurance.

1.2.1 Equilibrium under Symmetric Information

Consider first the market for private health insurance. Under symmetric information, private insurers know the risk of each applicant and can offer a corresponding contract. Following Rothschild and Stiglitz (1976), competition drives insurance companies to offer n actuarially fair contracts, one for each type, where each contract offers full insurance.

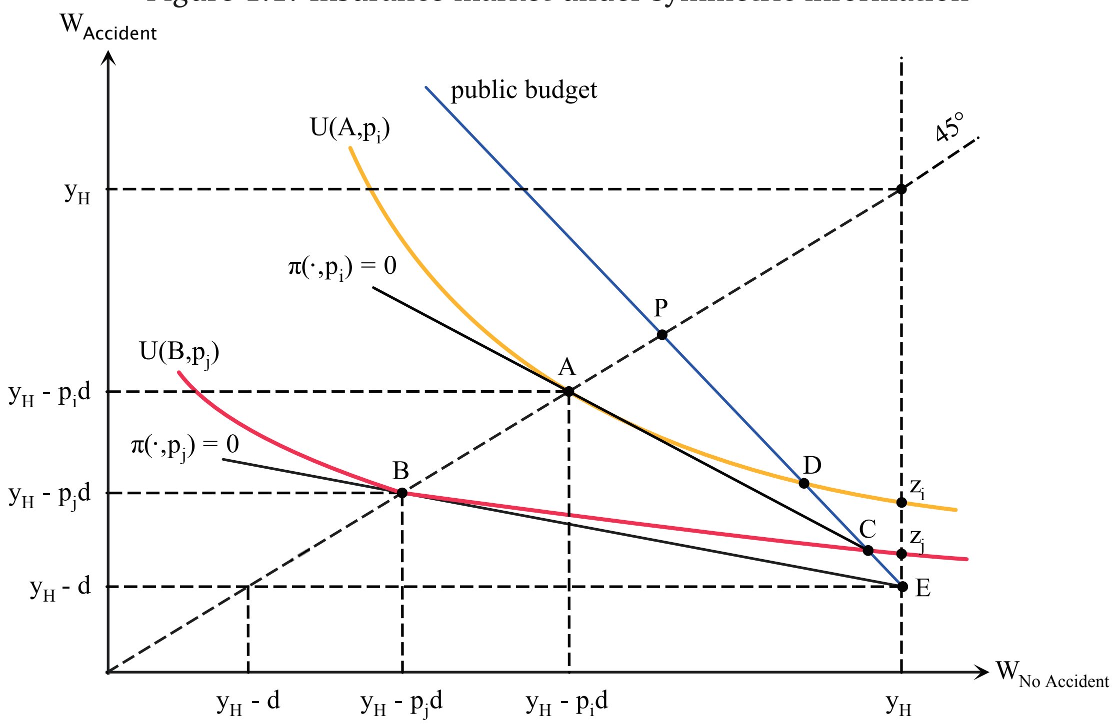
When deciding between public and private health insurance, the high-income earners take into account two factors: co-insurance rates and premiums. Since the high-income earners are risk averse, they tend to prefer low co-insurance rates. Furthermore, individuals prefer to pay the lowest price possible for a given amount of insurance coverage. For an individual of type p_i, the premium differential between public and private insurance is determined by the difference between incomes, which determines the amount of income redistribution, and the difference between p_i and the average risk in public insurance, which determines the gains from risk pooling.

The following lemma shows that the incentives to join public insurance are stronger for individuals with bad health, the intuition being that these individuals experience higher gains from risk pooling in public insurance.

Lemma 1. *For any given public plan under symmetric information, if p_i joins public insurance, then all types $p_j > p_i$ join public insurance.*

After performing the standard change of variables (see the Online Appendix) in Figure 1.1, the insurance contracts of two types $p_i < p_j$ are depicted in the space of final wealths. In the proof of Lemma 1, I show that the indifference curve of p_i through his designated private

Figure 1.1: Insurance market under symmetric information



Notes: $A = (p_i d, 0)$ and $B = (p_j d, 0)$, respectively, are the private insurance contracts offered to two risks p_i and p_j, where $p_i < p_j$. For a given contribution rate τ, the public insurance contract lies on the line EP. The exact position on EP depends on the co-insurance rate of the public plan. Full insurance ($\eta = 0$) corresponds to P and no insurance ($\eta = 1$) to E. z_i and z_j are used in the proof of Lemma 1.

insurance contract, A, lies strictly above the one of type p_j through his designated private contract, B. Assuming that the public insurance budget is balanced on the line running through the points E and P, we can see that both types join public insurance if the public plan is located on or above D, only p_j joins public insurance if the public plan is located on or above C and below D, and none of the two types joins public insurance if the public plan is located below C. This leads us to the health insurance market equilibrium.

Proposition 1. *Fix a co-insurance rate η for the public plan and suppose that some high-income earners choose to remain in public insurance. The health insurance market equilibrium under symmetric information, if it exists, is unique and characterised by a threshold type p_j, $p_1 < p_j \leq p_n$. The equilibrium strategy profile is such that $s^*(p_i) = 0$ for all $p_i < p_j$ and $s^*(p_k) = 1$ for all $p_k \geq p_j$, and the equilibrium set of contracts is the following:*

$$C^* = \left\{ I^{pub} = \left((1-\eta)\, d \frac{\lambda_L p_L + \sum_{k=j}^{n} \lambda_k p_k}{\lambda_L y_L + \sum_{k=j}^{n} \lambda_k y_H} y, \eta \right), I^{priv} = (p_i d, 0)_{i \in \{i : s^*(p_i) = 0\}} \right\}.$$

The public plan is adversely selected in this equilibrium since only the bad risks remain in public insurance.[3] Formally, $\mathbb{E}_p[pd \mid s^*(p) = 1] = \mathbb{E}_p[pd \mid p \geq p_j] > \mathbb{E}_p[pd]$, where the inequality follows from the fact that $p_j > p_1$. The healthiest high-income earners do not join public insurance in equilibrium because they have nothing to gain from risk pooling.

1.2.2 Equilibrium under Asymmetric Information

Now consider the case in which the insureds are privately informed about their personal risk, while the insurers only know the distribution of risks in the population. Let us again focus first on the private sector and abstract away from the public plan for a moment. From Rothschild and Stiglitz (1976), we know that, in equilibrium, less risky types will be offered contracts with higher co-insurance rates, competition drives profits on each contract down to zero, and contracts have to be separating; otherwise, there would exist a profitable deviation that lies in cream-skinning the good risks out of a pooling contract. We also know that the Rothschild-Stiglitz contracts are not generally second-best efficient,[4] and that an equilibrium

[3] The existence disclaimer in Proposition 1 is necessary because there are parameter constellations for which the government cannot set a budget-balancing contribution rate for a given amount of coverage in public insurance. This is due to the discreteness of the type distribution, which implies that the entry of any type into public insurance has a discrete effect on the public budget. It could be circumvented by allowing for mixed strategies or a continuum of types, but the model's conclusions would not be altered and the exposition be more cumbersome. To close the model, I assume that if the parameter constellation is such that there does not exist an equilibrium according to Definition 1, the government does not maintain a balanced budget and finances the budget gap out of general tax revenues.

[4] This is due to the requirement that each contract breaks even. Allowing for cross subsidisation, as in Wilson (1977), Miyazaki (1977), and Spence (1978), restores second-best efficiency, but cross subsidisation is a somewhat counterintuitive outcome in a competitive market (see, e.g., Mimra and Wambach 2014).

in pure strategies may fail to exist.[5]

The equilibrium properties of the private contract schedule remain basically unchanged in the presence of a public plan. The only difference is that, with a coexisting public plan, some incentive-compatibility constraints are not determined by making a type indifferent between two private contracts, but between a private contract and the public plan.

When deciding between public and private insurance, high-income earners face the same trade-off as under symmetric information. They weigh the difference in coverage between public and private insurance against the public-private premium differential. Only that now, under asymmetric information, coverage in private insurance is no longer necessarily higher than coverage in public insurance. This feature gives rise to the possibility of advantageous selection into public insurance, as can be seen in the following proposition.

Proposition 2. *Fix a co-insurance rate η for the public plan and suppose that some high-income earners choose to remain in public insurance. The health insurance market equilibrium under asymmetric information, if it exists, can feature two scenarios:*

1. *Adverse selection: there exists a threshold type p_j, $p_1 < p_j \leq p_n$,* such that $s^*(p_i) = 0$ *for all $p_i < p_j$* and $s^*(p_k) = 1$ *for all $p_k \geq p_j$, and the equilibrium set of contracts is*

$$C^* = \left\{ I^{pub} = \left((1-\eta)\, d \frac{\lambda_L p_L + \sum_{k=j}^{n} \lambda_k p_k}{\lambda_L y_L + \sum_{k=j}^{n} \lambda_k y_H} y, \eta \right), I^{priv} = \left(p_i\,(1-\beta_i)\,d, \beta_i\right)_{i \in \{i : s^*(p_i)=0\}} \right\},$$

where $I_i^{priv} = (p_i(1-\beta_i)d, \beta_i)$ is the private contract which will be chosen by type p_i.

2. *Nonmonotone selection: there exist two threshold types, p_j and p_k, $p_1 < p_j \leq p_k < p_n$, such that $s^*(p_i) = 0$ for all $p_i < p_j$, $s^*(p_r) = 1$ for all $p_j \leq p_r \leq p_k$, and $s^*(p_l) = 0$ for all $p_l > p_k$, and the equilibrium set of contracts is*

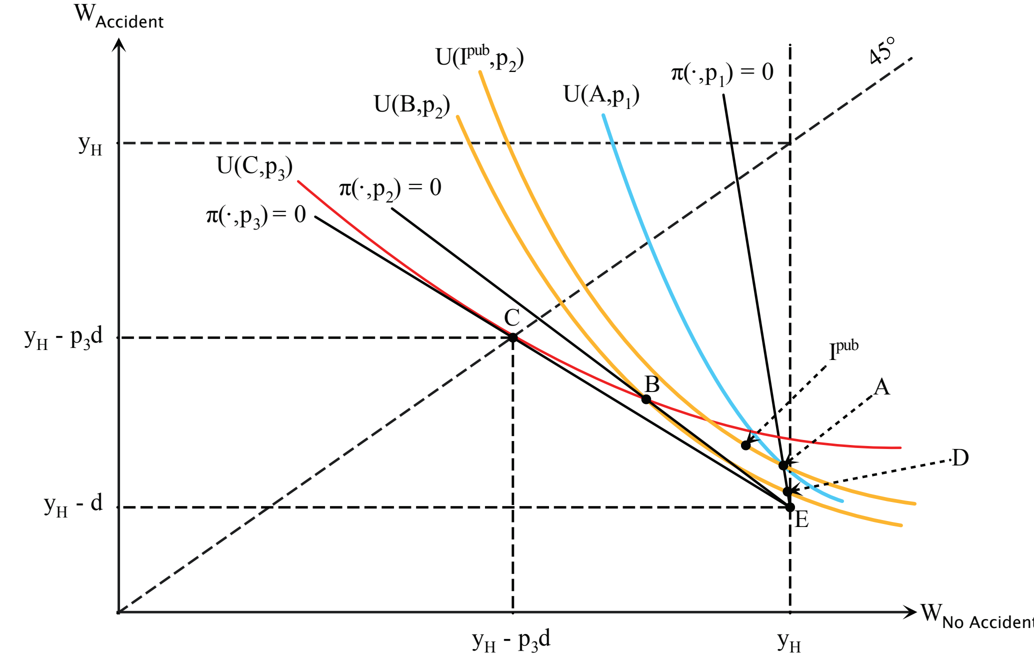
$$C^* = \left\{ I^{pub} = \left((1-\eta)\, d \frac{\lambda_L p_L + \sum_{r=j}^{k} \lambda_r p_r}{\lambda_L y_L + \sum_{r=j}^{k} \lambda_r y_H} y, \eta \right), I^{priv} = \left(p_i\,(1-\beta_i)\,d, \beta_i\right)_{i \in \{i : s^*(p_i)=0\}} \right\},$$

where $I_i^{priv} = (p_i(1-\beta_i)d, \beta_i)$ is the private contract which will be chosen by type p_i.

The equilibrium schedule of private contracts satisfies the following: (i) uniqueness: I^{priv} is unique, (ii) no distortion at the top: if $s^*(p_n) = 0$, then $\beta_n = 0$, (iii) *distortion at the bottom: if $s^*(p_i) = 0$ and $p_i < p_n$, then $\beta_i > 0$, (iv) incentive compatibility: if $s^*(p_i) = s^*(p_{i+1}) = 0$, then $U[(p_{i+1}(1-\beta_{i+1})d, \beta_{i+1}), p_{i+1}] = U[(p_i(1-\beta_i)d, \beta_i), p_{i+1}]$,* and *if $s^*(p_i) = 0$ and $s^*(p_{i+1}) = 1$, then $U(I^{pub}, p_{i+1}) = U[(p_i(1-\beta_i)d, \beta_i), p_{i+1}]$, (v) monotonicity: if $s^*(p_i) = s^*(p_j) = 0$ and $p_j > p_i$, then $\beta_j < \beta_i$, and (vi) positive insurance: if $s^*(p_i) = 0$, then $\beta_i < 1$.*

[5] With two types, the unique equilibrium ceases to exist when there are too many low risks. With more than two types, the conditions for equilibrium existence are more demanding; Riley (1985) identifies sufficient conditions for this case.

Figure 1.2: Equilibrium under asymmetric information with nonmonotone selection



Notes: A, B, and C are the incentive-compatible, actuarially fair private insurance contracts offered to types p_1, p_2, and p_3, respectively, where $p_1 < p_2 < p_3$. I^{pub} is the public plan. Types p_1 and p_3 prefer private over public insurance. Type p_2 prefers public over private insurance. The incentive-compatible contract for type p_1, A, is designed such that type p_2 is indifferent between this contract and public insurance. In the absence of a public plan, private insurers would offer the contract D to type p_1.

The first scenario, adverse selection, is the unique market outcome when all participants are symmetrically informed. The second scenario, which I call nonmonotone selection, occurs exclusively under asymmetric information. Under asymmetric information, private insurers offer screening contracts, which include less coverage for the good risks. This can lead to a situation in which relatively healthy individuals, who are offered a contract with little coverage in private insurance, stay in public insurance, because they dislike the risk that comes with the private contract, whereas some relatively sick individuals, who are offered a private contract with generous coverage, choose private insurance. But, as under symmetric information, the healthiest high-income earners do not join public insurance, because private insurers are always able to design a contract that is only appealing to individuals of type p_1.

Figure 1.2 illustrates the second scenario for the case of three types, $p_1 < p_2 < p_3$. In equilibrium, type p_2 chooses public insurance, and types p_1 and p_3 purchase private insurance. The equilibrium set of contracts is given by $C^* = \{I^{pub}, A, C\}$. Depending on the distribution of types, selection into public insurance can be adverse or advantageous. Formally, $\mathbb{E}_p[pd \mid s^*(p) = 1] = p_2 d$ and $\mathbb{E}_p[pd] = (\lambda_1 p_1 + \lambda_2 p_2 + \lambda_3 p_3)d/(\lambda_1 + \lambda_2 + \lambda_3)$, so that the public plan is adversely selected if $\lambda_1(p_2 - p_1) > \lambda_3(p_3 - p_2)$ and advantageously selected if the reverse inequality holds.

One special feature of a parallel public and private health insurance market is that some types can obtain more comprehensive coverage than in a purely private health insurance market: In the example of Figure 1.2, the incentive-compatible contract that can be offered to type p_1 is A. In the absence of a public plan, private insurers must reduce the coverage for type p_1 to the level of contract D, in order to guarantee incentive compatibility.

Against the common expectation that private health insurers will cream skim the best risks and leave the bad risks in public insurance, the model shows that selection between public and private insurance depends on the informational scenario. Corollary 1 summarises the model's predictions, which provide the basis for the test of asymmetric information that will be performed later on.

Corollary 1. *Under symmetric information, health status and health insurance choice are monotonously related, and the public plan is adversely selected. Under asymmetric information, the relationship between health status and health insurance choice can be monotone or U-shaped, and the public plan can be adversely or advantageously selected.*

The welfare consequences of asymmetric information under public health insurance with opt-out are ambiguous and depend on the type of selection into public insurance. If asymmetric information reduces adverse selection into public insurance, or even leads to advantageous selection into public insurance, then all low-income earners are better off and some high-income earners (those who receive less coverage in private insurance) are worse off than under symmetric information. This result stands in contrast to the welfare consequences of asymmetric information in a purely private market for health insurance, in which asymmetric information unambiguously reduces welfare.

1.3 Public Health Insurance with Opt-out in Germany

About 85% of the German population holds public health insurance, which is provided by non-profit insurers, so-called *sickness funds*. Public health insurance is largely financed through the contribution of its members, though a small part of the cost (less than 5%) is financed through general taxation. While public insurance is mandatory for the majority of the population, certain groups are allowed to opt out and buy substitutive private health insurance. Opting out of public insurance becomes possible when gross labor income is above the so-called *compulsory insurance threshold* (53,550 Euros in 2014), or when an individual is exempt based on his occupation. The two most important occupation groups that are exempt from the public insurance mandate are civil servants and the self-employed. About 15% of the population has decided to opt out and holds substitutive private health insurance, which is provided by for-profit insurance companies. Once an individual opts out of public insurance, reentry into the public system is restricted and becomes possible only when the criteria that determine eligibility to opt out are no longer satisfied.[6]

The most important difference between public and private health insurance lies in the premium calculation. Premiums in public insurance depend only on labor income. Publicly insured employees pay a fraction of their gross wage (8.2% in 2014) up to the *contribution ceiling* (48,600 Euros in 2014), above which contributions are zero. The employee contribution is matched with a contribution of similar size from the employer (7.3% in 2014), which is also paid if the employee decides to become privately insured. The contribution rate for the self-employed is equal to the sum of the employee and employer contribution, so that the self-employed have stronger incentives, c.p., to choose private insurance. Premiums in private insurance are risk rated and not tied to income. They are fixed at the initial enrollment and cannot be adjusted in response to health shocks after a contract has been signed. Moreover, private contracts are lifetime contracts and cannot be cancelled by the insurer unless premiums are not paid. Therefore, private insurance clients are, for the most part, protected against reclassification risk.

Risk rating in private insurance is conducted on the basis of mandatory health questionnaires.[7] Most insurers elicit the same information from potential consumers. Applicants have to report height and weight, disability status, chronic diseases, pregnancy status, a potential HIV infection, ambulatory treatments within the last three years, stationary treatments within the last five years, prescribed pharmaceuticals within the last 3 years, absences from work during the last three years, and psychological therapies within the last 10 years. Based on this information, insurers can apply risk surcharges or deny coverage for certain diseases or chronic conditions.

Contract customisation is another important aspect in which public and private insurance differ. Private insurance customers can select a contract that is individually optimal. Private insurers typically offer several benefit packages and annual deductibles; some private contracts also include co-insurance rates. Public insurance, on the other hand, offers little room for consumer choice. Almost all of the benefits that are covered by public health insurance are dictated by the regulator, and consumers do not have much choice in changing the cost-sharing rules of their contract. The standard public health insurance contract imposes little out-of-pocket expenses on its customers, which arise from moderate co-payments for pharmaceuticals and hospital stays.

When individuals choose between public and private health insurance, the relative price of the two plays a key role. This relative price depends on several factors. Most importantly, the relative price of public insurance increases with health status, since private premiums decrease with health and public premiums do not depend on health. The relative price of public

[6] Individuals above the age of 54 cannot switch from private to public insurance under any circumstances.

[7] As false reporting in the questionnaires can lead to withholding of benefits or termination of the contract, private insurance applicants have strong incentives to answer truthfully.

insurance decreases in age for two reasons. First, health deteriorates so that risk surcharges may apply. Second, private insurers are legally mandated to build up old-age provisions in order to keep premiums constant over the life-cycle. As the time period over which these old-age provisions can be built up becomes shorter the older the applicant, premiums increase. Public insurance is relatively cheap for families since non-working spouses and dependent children below 26 years of age are insured free of charge in public insurance. Women face a lower relative price of public insurance than men because private insurers charge women higher premiums throughout the sample period.[8] Civil servants pay a high relative price for public insurance because they and their dependent family members receive partial reimbursements of medical expenses through the so-called *Beihilfe*, which reduces the cost of private insurance by up to 80% but does not affect the price of public insurance. Self-employed individuals pay a high relative price for public insurance since they bear both the employer and employee contribution towards public insurance. The relative price of public insurance increases with the income of self-employed individuals and civil servants until the *contribution ceiling* is reached. Individuals who qualify to opt out of public insurance based on their income pay a fixed premium for public insurance since the *compulsory insurance threshold* lies above the *contribution ceiling*.

1.4 Data and Descriptive Statistics

The empirical analysis is based on data from the SOEP, a long-running panel which elicits information from a representative sample of households living in Germany. At the individual level, the SOEP contains subjective and objective health measures, health insurance details, as well as a wide array of socio-economic variables.

The sample period covers the years from 1998 to 2011; though information from 2011 is only used to calculate insurance status in 2010.[9] The sample consists of individuals aged 20 to 65 who are eligible to purchase private insurance, are not insured through one of their family members, and switch insurance status at most once. Individuals under 20 of age are excluded to avoid distortions which may arise from family insurance. Individuals above the age of 65 are excluded because they are unlikely to consider switching to private insurance due to prohibitively high premiums caused by risk adjustment and missing old-age provisions. Individuals who are insured through one of their family members are excluded because they do not make an active decision. Individuals who switch their insurance status more than once are excluded because these switches likely represent misreporting of insurance status, given that switching from private to public insurance is heavily regulated. Individuals in the sample

[8]However, as of December 2012, gender-based discrimination of insurance premiums is prohibited in the European Union by a ruling of the European Court of Justice.

[9]Observations from prior to 1998 had to be excluded because important controls are missing.

Table 1.1: Descriptive statistics of selected variables

Health measures	Public	Private	Socio-economic factors	Public	Private
Self-assessed health	3.586	3.647	Female	0.247	0.300
	(0.837)	(0.824)		(0.431)	(0.458)
Disability	0.054	0.043	Age	44.891	46.170
	(0.226)	(0.202)		(9.630)	(9.628)
Sick leave >6 weeks	0.094	0.056	Married	0.738	0.692
	(0.292)	(0.229)		(0.440)	(0.462)
Hospitalised	0.080	0.078	Children in household	0.782	0.633
	(0.271)	(0.268)		(1.028)	(0.916)
Nights in hospital	0.817	0.724	Self-employed	0.272	0.304
	(5.120)	(4.692)		(0.445)	(0.460)
Doctor visits per quarter	1.867	2.041	Civil servant	0.025	0.446
	(3.190)	(3.730)		(0.155)	(0.497)
N	21,172	16,606	*N*	21,172	16,606

Notes: Means and standard deviations (in parentheses) are calculated based on all observations from 1998 to 2010 of individuals aged 20 to 65 who are eligible to purchase private insurance, are not insured through one of their family members, and do not switch insurance status more than once. Two-sided t-tests reject the null hypothesis of no difference in means between public and private insurance at the 1% level of significance for all variables except hospitalised (p=0.542) and nights in hospital (p=0.068). Number of observations varies by variable and sample.

are self-employed, civil servants, or have incomes above the *compulsory insurance threshold*. In total, there are 38,633 person-year observations from 8,310 individuals. Out of those, 494 individuals (5.9%) opt out of public insurance.

Table 1.1 contains means and standard deviations of selected variables stratified by insurance status. From these statistics, we can infer that the privately insured appear to be healthier: they have better self-reported health, and they are less likely to be disabled and to take a sick leave of more than six weeks within a year. On the other hand, the privately insured seem to consume slightly more medical care: they go more often to the doctor, they are about equally likely to be hospitalised within a year, and they spend roughly the same amount of nights in the hospital. With regard to the socio-economic characteristics, private insurance clients are older and more likely to be female, which stands in contrast to the institutional incentives. In accordance with the institutional incentives, the privately insured have fewer children, are less likely to be married, and are more likely to be self-employed or civil servants.

1.5 Empirical Strategy

The first goal of the empirical analysis is to identify the nature of selection between public and private health insurance, which will be inferred from the correlation of the error terms in a bivariate probit model of health insurance choice (public or private) and subsequent healthcare use that includes no controls. In a second step, I decompose selection into a part that is due to observable characteristics of insureds which affect the relative price between public and private insurance and a part that is due other factors. To this end, I include observable characteristics of insureds that determine the relative price between public and private insurance as independent variables in the bivariate probit model of healthcare utilisation and health insurance choice. The results of this decomposition should be of particular interest to policymakers who want to reduce selection, since the two selection components require different approaches.

However, as is well known, the correlation of the error terms in a bivariate probit model of health insurance choice and healthcare use, with or without controlling for observables, can reflect both moral hazard and adverse selection. To address this issue, I choose a measure of healthcare use that is arguably less susceptible to moral hazard: hospitalisations. Patients generally do not choose to become hospitalised considering the financial consequences of the hospitalisation; frequently the patient's medical condition is so severe that a hospitalisation is inevitable, or the physician, and not the patient, decides about the hospitalisation.[10] The

[10] Early empirical support for the hypothesis that hospitalisations are not affected by moral hazard stems from the RAND Health Insurance Experiment (Manning *et al.* 1987). The recent Oregon Health Insurance Experiment finds evidence of moral hazard in hospitalisations (Finkelstein *et al.* 2012), but in subjects who predominantly earn low incomes. For a variety of reasons, these individuals may react differently to health insurance coverage

validity of the empirical approach hinges on the identifying assumption that hospitalisations do not depend on health insurance status (public or private) other than through selection.

There are several reasons why the identifying assumption is particularly reasonable in the context of the German health insurance system. First, the cost of a hospitalisation is roughly the same for privately and publicly insured patients.[11] This implies that, even if people have a price elasticity of demand for hospitalisations which is different from zero, the moral hazard effect of health insurance should be modest. Second, several studies have examined the incentive effect of private health insurance coverage on hospitalisations in Germany, all of which conclude that there is no statistically significant effect.[12] Finally, there are no supply-side incentives at work, since payment rates for hospital care are the same for publicly and privately insured patients.

Following Bünnings and Tauchmann (2015), I model health insurance choice as a hazard model in discrete time with private insurance as the absorbing state, i.e., individuals enter the estimations only up to the point at which they choose to become privately insured. The dependent variable OPTOUT_{it} equals zero as long as an individual chooses to remain in public insurance. OPTOUT_{it} equals one in the period before an individual first reports to be privately insured, which is done in order to guarantee that the independent variables are predetermined. In all other cases, OPTOUT_{it} is set to missing. German legislation dictates the choice of a hazard model, as it generally restricts private insurance clients to stay in private insurance.

I estimate variants of the following bivariate probit model:

$$\text{OPTOUT}_{it} = \mathbf{1}\left(a_1 + b_1 X_{it} + c_1 Z_{it} + e_{1it} > 0\right). \tag{1.2}$$

$$\text{HOSPITAL}_{it+1} = \mathbf{1}\left(a_2 + b_2 X_{it} + c_2 Z_{it} + e_{2it} > 0\right). \tag{1.3}$$

HOSPITAL_{it+1} is an indicator that equals one if individual i is hospitalised in period $t+1$, the baseline measure of healthcare use. X_{it} is a vector of observable attributes of individual i that determine the relative price between private and public insurance at time t.[13] Z_{it} is a vector

than the individuals who qualify to opt out in Germany.

[11]The publicly insured pay a copayment of 10 Euros per day of hospital stay, up to a maximum of 280 Euros a year. The most common form of cost sharing in private insurance is a deductible, where the most popular deductibles are, in that order, 0 Euros, 300 Euros, and 600 Euros.

[12]The two most convincing studies are by Hullegie and Klein (2010) and Polyakova (2014), who exploit the *compulsory insurance threshold* in a regression discontinuity design, with which the authors can control for selection into public and private health insurance. Using SOEP data, both studies find no incentive effect of health insurance status on hospital stays. Two earlier studies also do not find an effect of the type of health insurance on hospitalisations (Geil *et al.* 1997, Riphahn *et al.* 2003).

[13]X contains disability status, the probability of a hospitalisation, the number of hospitalisations, and the number of days spent in the hospital for the last five years, the number of doctor visits for the last three years, absences from work for more than six weeks for the last three years, number of children in household, marital status, gender, an indicator of being a women of child-bearing age, five-year age band dummies, an indicator of self-employment, an interaction term between self-employment and the logarithm of income, an indicator of

of unused observables and will be described in more detail below.

The error terms $e_{it} = (e_{1it}, e_{2it})$ are assumed to be independently, identically, and normally distributed across individuals. They may, however, be correlated over time for a given individual. In the main analysis, I will estimate a pooled bivariate probit model with standard errors clustered at the individual level. Because some individuals may decide to stay in public insurance once and for all when they become eligible to opt out of public insurance, without reevaluating the relative price between public and private insurance in future periods, I will, as a robustness check, estimate the bivariate probit model on the subsample of individuals who are in their first or second year of being eligible to opt out.

In a first step, I will estimate the bivariate probit model with $b = (b_1, b_2) = 0$ and $c = (c_1, c_2) = 0$ imposed. The correlation between the error terms in this specification reveals the total extent of selection between public and private insurance. Subsequently, I will estimate the bivariate probit model with $c = 0$ imposed, which is akin to the standard positive correlation test (Chiappori and Salanié 2000). The correlation between the error terms in this specification reflects the part of selection that is not related to the relative price between public and private insurance. We can then back out the effect of the relative price between public and private insurance from the difference in the correlation coefficient between the model without controls and the model which controls for observables. Following this decomposition, I turn to identifying the sources of selection by including unused observables in the bivariate probit model (Finkelstein and Poterba 2014). Finally, I use a source of private information about health status to test for asymmetric information exploiting the predictions of the theoretical model.

1.6 Results

1.6.1 Magnitude and Sources of Selection

Table 1.2 reports the correlation of the residuals from the bivariate probit model, with and without controlling for observables that determine the relative price between public and private insurance. The results for the full sample, which are shown in column 1, indicate that public insurance is adversely selected on balance: individuals who opt out of public insurance in period t are significantly less likely to be hospitalised in period $t+1$, as evidenced by the negative correlation coefficient of the bivariate probit model without controls. Once we control for observable differences across individuals that affect the relative price between private and public insurance, there remains less unexplained correlation between the choice to opt out and future hospitalisations. However, since the residual correlation is still negative and statistically significant, we can conclude that it is not only the relative price between public

being a civil servant, an interaction term between civil servant and the logarithm of income, and a set of year dummies.

Table 1.2: Magnitude of selection

	Full sample (1)	High income (2)	Civil servants (3)	Self-employed (4)
Panel A: No controls				
$\hat{\rho}$	-0.151***	-0.169***	0.103	-0.190**
Wald test of $\rho = 0$ (p-value)	(0.001)	(0.002)	(0.547)	(0.046)
Panel B: Control for observables				
$\hat{\rho}$	-0.098*	-0.101	0.150	-0.119
Wald test of $\rho = 0$ (p-value)	(0.055)	(0.108)	(0.546)	(0.274)
N	12,767	8,438	338	3,991

Notes: Table reports correlations of the residuals from bivariate probit estimations of equations (1.2) and (1.3) and p-values (in parentheses) of Wald tests of $\rho = 0$. Panel A reports correlations from the model with $b = c = 0$. Panel B reports correlations from the model with $c = 0$. Column 1 reports correlations for the whole sample. Column 2 reports correlations for the subsample of individuals who qualify to opt out of public insurance solely based on income. Columns 3 and 4, respectively, report correlations for the subsample of civil servants and self-employed, respectively. p-values are based on standard errors which are clustered at the individual level. * p<0.1, ** p<0.05, *** p<0.01.

and private insurance that gives rise to adverse selection into public insurance but also other factors. Comparing the size of the two correlation coefficients, we see that the relative price between public and private insurance actually accounts for only about one-third ($-0.151 + 0.098 = -0.053$) of the total extent of adverse selection into public insurance, the other two-thirds (-0.098) being accounted for by other factors.

Since the institutional setup is such that civil servants and the self-employed have stronger incentives to join private insurance than those who qualify to opt out of public insurance solely based on income, I stratify the preceding results by eligibility criterium. The corresponding estimates, which are shown in columns 2-4 of Table 1.2, show that the results for the self-employed and income-rich are similar and coincide with the results for the whole sample, while the results for the subsample of civil servants are diametrically opposed. We observe a positive and statistically insignificant unconditional correlation between the choice to opt out of public insurance and future hospitalisations for civil servants. Since almost all civil servants join private insurance, it is perhaps no surprise that private insurers cannot select civil servants who are better risks. The effect of the relative price between public and private insurance on civil servants is negative but small (-0.047). This could be a result of the fact that civil servants pay only a fraction of their private insurance premium, which makes them less price sensitive.

Having established the existence of adverse selection into public insurance, the next logical question is: what drives this selection? To answer this question, I follow Finkelstein and Poterba (2014) and search for unused observables that are correlated with both health insurance choice and healthcare use after controlling for observables, where unused observables are variables that do not affect the relative price between public and private health insurance but which are observed by the econometrician. Table 1.3 reports results for three unused observables that matter for selection between public and private health insurance: self-assessed health, risk aversion, and residential location. Several other unused observables, including smoking status, education, frequency of sport/exercise, hours of work, and income, do not explain selection, since they are not correlated with both health insurance choice and healthcare use after controlling for observables.

Self-assessed health is reported on a five-point scale from one (=very bad) to five (=very good) and explains a part of the adverse selection against the public sector: after controlling for observables, individuals with higher self-assessed health are less likely to be hospitalised and more likely to choose private insurance. This self-selection of consumers is consistent with the idea that private insurers screen their applicants. Healthy individuals choose private contracts with high deductibles, in return for low insurance premiums, whereas sick individuals prefer public insurance, which involves moderate cost sharing. One caveat applies to this result, however. The observables which are included in X can potentially not control for all the differences between individuals that affect the relative price between public and private health insurance. It could be, therefore, that self-assessed health picks up a part of the effect of the observables, meaning that the coefficients above are an upper bound on the impact of the unobservable (for insurers) part of health status on health insurance choice and hospitalisations. I will return to this issue in Section 1.6.3.

The second source of selection is risk aversion, which is reported on a scale from zero to ten, where individuals are asked to assess their aversion towards risk in general.[14] I follow Bünnings and Tauchmann (2015) and others and consider risk preferences as fixed over time, using the average value of an individual's responses. Table 1.3 shows that risk aversion gives rise to advantageous selection in favour of the public sector: after controlling for observables, risk-averse individuals are less willing to opt out of public insurance and less likely to be hospitalised. Switching to private insurance implies uncertainty about future premiums, as changes in family status translate into premium changes in private insurance. For example, a privately insured couple who become parents has to pay for their child in private health insurance, whereas the child is insured free of charge in public insurance. This may explain why risk-averse individuals prefer public insurance. The finding that risk-averse individuals tend to be less risky has been observed also in other contexts (Finkelstein and McGarry 2006). Possible explanations for this result are that the risk averse use more preventive care, or that

[14]Dohmen *et al.* (2011) confirm that this question is a good measure of risk aversion in several domains.

Table 1.3: Sources of selection

	(1)	(2)	(3)	(4)
Dependent variable: OPTOUT				
Self-assessed health	0.005**			0.003
	(0.002)			(0.002)
Risk aversion		-0.003***		-0.003***
		(0.001)		(0.001)
West Germany			-0.025***	-0.026***
			(0.004)	(0.004)
Dependent variable: HOSPITAL				
Self-assessed health	-0.028***			-0.029***
	(0.003)			(0.003)
Risk aversion		-0.003**		-0.004***
		(0.001)		(0.001)
West Germany			-0.011*	-0.011*
			(0.006)	(0.006)
N	12,757	12,010	12,767	12,001

Notes: Table reports average marginal effects of three unused observables from bivariate probit estimations of equations (1.2) and (1.3). Coefficient estimates for the observables (X) are suppressed. Means of OPTOUT and HOSPITAL vary across columns. Standard errors adjusted for clustering at the individual level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

they abstain from undertaking risky activities.

The final source of selection is residential location. Individuals who reside in the states of former West Germany advantageously select public insurance. Consequently, individuals living in the states of former East Germany adversely select public public insurance. Since the former are more numerous (361 residents of West Germany opt out vs. 133 residents of East Germany), residential location leads to advantageous selection into public insurance on average. Whether this selection is driven by consumers or insurers cannot be answered in the present framework and with the available data. Bauhoff (2012) shows that supply-side selection on geographic location exists, suggesting that the latter is driving the results to some extent. Heterogeneous consumer preferences may also play a role, but Bünnings and Tauchmann (2015) show that, except for risk aversion, personality traits do not appear to affect insurance choice.

Table 1.4: Testing for asymmetric information

Dependent variable:	OPTOUT		HOSPITAL	
SAH=1	0.010	(0.018)	0.057*	(0.034)
SAH=2 (omitted)	0.000	—	0.000	—
SAH=3	0.014**	(0.006)	-0.044***	(0.011)
SAH=4	0.014**	(0.005)	-0.074***	(0.011)
SAH=5	0.022***	(0.007)	-0.083***	(0.012)
N	12,757		12,757	

Notes: Table reports average marginal effects of the five categories of self-assessed health from bivariate probit estimations of equations (1.2) and (1.3). Coefficient estimates for the observables (X) are suppressed. 1=very bad, 2=bad, 3=satisfactory, 4=good, 5=very good. Means of OPTOUT and HOSPITAL are 0.035 and 0.077, respectively. Standard errors adjusted for clustering at the individual level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

1.6.2 Testing for Asymmetric Information

The standard test of asymmetric information analyses the consumer's decision between two different insurance contracts, where one contract offers more generous coverage than the other, and the occurrence of subsequent risk events (Chiappori and Salanié 2000). In the present setting, however, individuals choose between public and private health insurance, which are not ordered by the level of coverage. We can therefore not proceed as usual.

Fortunately, the theoretical model of Section 1.2 offers a one-sided test of asymmetric information. Recalling Corollary 1, we know that both advantageous selection into public insurance and a U-shaped relationship between the choice of private insurance and unobservable (to the insurers) health status occur only under asymmetric information. Hence, either of the two indicates the presence of asymmetric information. Notice that since the model describes the situation within a risk cell, we have to control for observables that determine the relative price between public and private insurance to test for asymmetric information.

As we have seen in Table 1.2, the residuals are negatively correlated after controlling for observables, meaning that one of the two indicators of asymmetric information is not present. Nevertheless, we may still conclude that there is asymmetric information, in case we find a U-shaped relationship between health insurance choice and unobservable health status. Self-assessed health is a natural candidate to test for such a relationship, as it is likely to contain private information about health status. In order to pick up a potential nonmonotone effect of self-assessed health, I replace the previously considered linear term with indicators for the five categories of self-assessed health.

Table 1.4 shows the estimated average marginal effects of these five categories after controlling for observables. The probability that a hospitalisation occurs decreases strictly in self-assessed health, meaning that the residual information contained in self-assessed health is indeed predictive of health status. On the other hand, the probability of opting out of public insurance is nonmonotonously related to self-assessed health: the relationship is U-shaped, where the probability of opting out of public insurance is lowest for individuals with a self-assessed health status of two. According to the theoretical model, this U-shaped relationship indicates the presence of asymmetric information between private insurers and their clients. However, due to there being only a handful of observations in the lowest category of self-assessed health, the coefficient estimates for this category are very imprecise. In particular, the estimate from the opt-out equation is not statistically different from zero, so that the evidence in favour of information asymmetry should be considered as merely suggestive.

1.6.3 Robustness Checks

This section discusses potential threats to the validity of the empirical approach and examines the robustness of the conclusions to these threats. The detailed results of this sensitivity analysis are collected in Tables 1.6-1.8 in Appendix 1.B. The qualitative conclusions do not change in any of the alternative specifications. In fact, the results are often quantitatively similar to those of the baseline estimates. Notably also, the nonmonotone pattern between self-assessed health and health insurance choice is preserved in all of the alternative specifications. Nevertheless, due to large variations in the number of observations and corresponding variations in statistical power, the estimates' statistical significance occasionally departs from those of the baseline estimates.

The most pressing issue is the potential mismatch between the actual observables that determine the relative price between public and private and the observables which are taken into account in the empirical analysis. Some variables in the SOEP are less informative than the corresponding questions from the insurer questionnaires. Moreover, some items from the insurer questionnaires are not included in the SOEP, or they are included only in some years. Private insurers could thus have more information about insurance applicants than what is controlled for with the vector of observables. To assess the extent of this issue, I have regressed private health insurance premiums on the vector of observables. Encouragingly, the estimates from this regression, which are available upon request, show that X explains a large fraction of the variation in private health insurance premiums, even without taking into account differences in benefits packages and cost sharing. I therefore argue that the vector X provides a reasonable approximation to the actual variables that determine the relative price between public and private insurance. I moreover perform a couple of robustness checks in which X includes further health-related variables, such as the existence of chronic conditions and the physical and mental component scales described in Andersen *et al.* (2007).[15]

Another issue is that some individuals may only actively consider opting out of public insurance in the first few periods when they become eligible to opt out. In order to show that the estimates are not driven by repeated observations on individuals who do not make an active decision between public and private insurance, I perform a robustness check on the subsample of individuals who are in the first or second year of being eligible to choose private insurance.

Next, I assess the measure of healthcare use of the baseline model, which is an indicator that equals one if an individual is hospitalised in the year after the making choice between public and private insurance. I consider two alternatives measures of healthcare use. First, I construct an indicator that equals one if an individual is hospitalised in period $t{+}1$ or $t{+}2$. This indicator addresses the issue that hospitalisations are rare, meaning that there are relatively few observations where the dependent variable HOSPITAL equals one. Second, I construct an indicator that equals one if an individual stays three or more nights in the hospital in period $t + 1$. This indicator addresses the issue that hospitalisations differ in terms of the severity of illness of the patient, which is not accounted for in the baseline regressions.[16]

Finally, there appears to be some measurement error in income in the SOEP data (see, e.g., Hullegie and Klein 2010). To address this issue, I perform a robustness check in which I exclude all individuals with income equal to zero (who can only be civil servants or self-employed) and keep only the self-employed, civil servants, and individuals with incomes of 5,000 above the *compulsory insurance threshold*, in order to guarantee that all individuals in the sample can actually choose to opt out of public insurance.

1.7 Conclusion and Discussion

There are a number of benefits associated to the German public health insurance with opt-out scheme. These include the socialisation of risks in public insurance vis-à-vis a system relying only on private health insurance, public insurance being an insurance of last resort to the seriously sick and the poor, a reduced number of insureds having double coverage compared to a system with a national health service such as the UK, and an increased competition for clients, which creates strong incentives for public health insurance providers to increase efficiency and quality.

These benefits have to be weighed against the potential for adverse selection into public insurance. Since private health insurance premiums are based on individual risks and public health insurance contributions are not, private insurers are expected to attract observably

[15] Both variables are available only for a few years and therefore not included in the baseline regressions.

[16] In the baseline regressions, minor conditions, which may require just one or two nights in the hospital, are lumped together with the most severe health conditions, which may require weeks, or even months, of hospital care.

better risks. Moreover, private insurers may also attract unobservably better risks, through offering contracts with lower premiums and higher degrees of cost sharing than the public plan; though, as this paper shows, private insurers do not necessarily succeed in doing so when there is asymmetric information. Adverse selection can also become worse over time: if the healthy high-income earners switch to private insurance and the government raises premiums to compensate for the fact that the average risk in public insurance has gone up, more relatively healthy high-income earners may feel inclined to opt out. This process can develop in a similar fashion as the adverse selection death spiral described in Cutler and Zeckhauser (1998); though public insurance would not become extinct since the low-income earners cannot opt out.

Whether and to what extent public insurance is adversely selected is ultimately an empirical question. The evidence presented in this and other papers suggests that adverse selection is a serious issue in the German health insurance system. Those most affected by it are the low-income earners: they are mandatorily insured in public insurance and have to compensate the outflow of good risks from public to private insurance with higher contributions. For their benefit, it will thus be important that policymakers address the issue of adverse selection, so as to guarantee that public insurance can attract a diversified pool of risks in the future. In 2007, Germany introduced a reform that may mitigate adverse selection into public insurance. Since then, public health insurance providers are allowed to offer contracts with varying degrees of cost sharing, so-called *choice policies*. How this reform has affected risk selection in the German health insurance system remains an open question and could prove to be an interesting topic for future research.

Appendices

1.A Theory Appendix

1.A.1 Contracts in the Final Wealths Space

Insurance can be expressed in terms of the final wealths it implies. An individual with risk p_i and income y who has purchased the insurance contract $I = (\alpha, \beta)$ has final wealth $W_{NA} = y - \alpha$ if no accident occurs and final wealth $W_A = y - \beta d - \alpha$ in case of an accident. Solving for the premium and the co-insurance rate, we get that $\alpha = y - W_{NA}$ and $\beta = (W_{NA} - W_A)/d$. Hence, expected utility can be expressed as

$$U\left(W_{NA}, W_A, p_i\right) = p_i u\left(W_A\right) + \left(1 - p_i\right) u\left(W_{NA}\right),$$

and expected profits can be expressed as

$$\pi\left(W_{NA}, W_A, p_i\right) = y - W_{NA} - p_i\left(W_A - W_{NA} + d\right).$$

The marginal rate of substitution for a risk p_i in the point (W_{NA}, W_A) is equal to

$$\left.\frac{dW_A}{dW_{NA}}\right|_{U(W_{NA}, W_A, p_i)} = -\frac{1 - p_i}{p_i}\frac{u'\left(W_{NA}\right)}{u'\left(W_A\right)}. \tag{1.4}$$

Lemma 2 follows immediately from inspection of (1.4).

Lemma 2. *In any point* (W_{NA}, W_A)*,* $dW_A/dW_{NA}|_{U(W_{NA}, W_A, p_i)} < dW_A/dW_{NA}|_{U(W_{NA}, W_A, p_j)}$ *if and only if* $p_i < p_j$*.*

This means that the indifference curves of two different types can be ordered by steepness: the less riskier type has steeper indifference curves. Besides, if insurance is provided at actuarially fair or favourable odds, then more insurance is always better, as the following Lemma shows.

Lemma 3. *For* $0 < \beta < 1$*,* $U[(q(1 - \beta)d, \beta), p_i]$ *is strictly decreasing in* β *if* $q \leq p_i$*.*

Proof of Lemma 3. The partial derivative of $U[(q(1 - \beta)d, \beta), p_i]$ with respect to β is

$$\frac{\partial U\left[\left(q\left(1 - \beta\right) d, \beta\right), p_i\right]}{\partial \beta} = qd\left(1 - p_i\right) u'\left[y_H - q\left(1 - \beta\right) d\right] - p_i d\left(1 - q\right) u'\left[y_H - \beta d - q\left(1 - \beta\right) d\right].$$

Since $0 < \beta < 1$ and $u''(\cdot) < 0$, $u'[y_H - \beta d - q(1 - \beta)d] > u'[y_H - q(1 - \beta)d]$. It is easy to check then that the partial derivative above is strictly negative for $q \leq p_i$.

Isoprofit curves in (W_{NA}, W_A)-space are straight lines with slope $-(1-p_i)/p_i$. The zero-profit line for an individual with risk p_i and income y is characterised by the following equation: $W_A = y/p_i - d - (1-p_i)/p_i W_{NA}$.

Public insurance leads to final wealths $W_{NA}^{pub} = y(1-\tau)$ and $W_A^{pub} = y(1-\tau) - \eta d$, respectively, in the case of no accident and in the case of an accident. Solving for τ and η, we get that $\tau = 1 - W_{NA}^{pub}/y$ and $\eta = (W_{NA}^{pub} - W_A^{pub})/d$. The public budget is balanced if

$$W_A^{pub} = \frac{\lambda_L y_L + \sum_{i=1}^{n} \lambda_i s\left(p_i\right) y_H}{\lambda_L p_L + \sum_{i=1}^{n} \lambda_i s\left(p_i\right) p_i} - d - W_{NA}^{pub} \left(\frac{1}{y} \frac{\lambda_L y_L + \sum_{i=1}^{n} \lambda_i s\left(p_i\right) y_H}{\lambda_L p_L + \sum_{i=1}^{n} \lambda_i s\left(p_i\right) p_i} - 1 \right).$$

Hence, for a given strategy profile $s = [s(p_i)]_{i\in\{1,\ldots,n\}}$, feasible allocations under the public insurance plan are located on a straight line in (W_{NA}, W_A)-space. The slope of this line depends on the characteristics of those individuals who join public insurance:

$$\frac{dW_A^{pub}}{dW_{NA}^{pub}} = -\left(\frac{1}{y} \frac{\lambda_L y_L + \sum_{i=1}^{n} \lambda_i s\left(p_i\right) y_H}{\lambda_L p_L + \sum_{i=1}^{n} \lambda_i s\left(p_i\right) p_i} - 1 \right).$$

The slope is flatter for high- than for low-income earners due to income redistribution.

1.A.2 Proofs

Lemma 1. *For any given public plan under symmetric information, if p_i joins public insurance, then all types $p_j > p_i$ join public insurance.*

Proof of Lemma 1. Consider any two types p_i and p_j, where $p_1 \leq p_i < p_j \leq p_n$. To prove the Lemma, it suffices to show that p_i's indifference curve lies strictly above p_j's indifference curve, within the insurance plane, when both types buy their designated private insurance contracts. Three observations conclude the proof. First, note that p_i's indifference curve lies above p_j's indifference curve on the upper left edge of the insurance plane, since $u(y-p_i d) > u(y-p_j d)$. Second, note that the indifference curves of two types cross at most once, since expected utility satisfies the Spence-Mirrlees strict single crossing property. Third and finally, I show that p_i's indifference curve lies above p_j's indifference curve on the right edge of the insurance plane, where $W_{NA} = y$. Following the proof provided in Olivella and Vera-Hernández (2013) and referring to Figure 1.1 on page 15, I want to show that $z_i > z_j$, where z_i and z_j satisfy the following:

$$\begin{aligned} u\left(y_H - p_i d\right) &= p_i u\left(z_i\right) + \left(1-p_i\right) u\left(y_H\right). \\ u\left(y_H - p_j d\right) &= p_j u\left(z_j\right) + \left(1-p_j\right) u\left(y_H\right). \end{aligned}$$

Since $u'(\cdot) > 0$, $z_j < z_i$ is equivalent to $u(z_j) < u(z_i)$. Hence, I want to show that:

$$u(z_j) = \frac{u(y_H - p_j d) - (1-p_j)\, u(y_H)}{p_j} < \frac{u(y_H - p_i d) - (1-p_i)\, u(y_H)}{p_i} = u(z_i)\,.$$

Rearranging terms, we obtain:

$$u(y_H - p_i d) > \frac{p_i}{p_j} u(y_H - p_j d) + \frac{p_j - p_i}{p_j} u(y_H)\,. \tag{1.5}$$

Denote $q = p_i/p_j$, $x_1 = y_H - p_j d$, and $x_2 = y_H$. Note that $q \in (0,1)$ and $\mathbb{E}_q(x) = q(y_H - p_j d) + (1-q)y_H = y_H - p_i d$. Hence, inequality (1.5) can be expressed as

$$u\left[\mathbb{E}_q(x)\right] > \mathbb{E}_q\left[u(x)\right],$$

which is true by Jensen's inequality and the assumption that $u(\cdot)$ is strictly concave.

The following result is used in the proof of Proposition 1.

Lemma 4. *No type chooses public insurance at actuarially unfavourable odds in the equilibrium under symmetric information: if $s^*(p_i) = 1$, then $p_i \geq \tau y_H/(1-\eta)d$.*

Proof of Lemma 4. Suppose, by contradiction, that there exists a type p_i who chooses public insurance at actuarially unfavourable odds in the equilibrium under symmetric information. If private insurers duplicate the public contract and sell it exclusively to p_i, abstracting for a moment from the tie-breaking assumption, then they would generate strictly positive profits. Then, there exists a contract $I = (\tau y_H - \varepsilon, \eta)$ that, if offered exclusively to type p_i, would attract all individuals of type p_i and generate nonnegative profits. This violates the third condition for equilibrium; contradiction.

Proposition 1. *Fix a co-insurance rate η for the public plan and suppose that some high-income earners choose to remain in public insurance. The health insurance market equilibrium, if it exists, is unique and characterised by a threshold type p_j, $p_1 < p_j \leq p_n$. The equilibrium strategy profile is such that $s^*(p_i) = 0$ for all $p_i < p_j$ and $s^*(p_k) = 1$ for all $p_k \geq p_j$, and the equilibrium set of contracts is the following*

$$C^* = \left\{ I^{pub} = \left((1-\eta)\, d \frac{\lambda_L p_L + \sum_{k=j}^{n} \lambda_k p_k}{\lambda_L y_L + \sum_{k=j}^{n} \lambda_k y_H} y, \eta \right), I^{priv} = (p_i d, 0)_{i \in \{i: s^*(p_i) = 0\}} \right\}.$$

Proof of Proposition 1. Lemma 1 and the assumption that some high-income earners choose to remain in public insurance imply that there exists a threshold p_j, $p_j \in \{p_1, \ldots, p_n\}$, such that

$s^*(p_i) = 0$ for all $i < j$ and $s^*(p_k) = 1$ for all $k \geq j$. For a given equilibrium strategy profile s^* and a given co-insurance rate η for the public plan, the contribution rate for public insurance, τ, is determined by the balanced budget condition in equation (1.1). I proceed in a series of steps. In *Step 1*, I show that only private contracts of the form $I^{priv} = (p_i d, 0)_{i \in \{1,\dots,n\}}$ can be in the equilibrium set of contracts, C^*. In *Step 2*, I show that type p_1 never joins public insurance in equilibrium. Finally, in *Step 3*, I show that the equilibrium is unique.

Step 1. Under symmetric information, the market for private health insurance is segmented. Hence, we can fix a type p_i. Suppose now, by contradiction, that there exists a private contract $I = (\alpha, \beta) \in C^*$, $I \neq (p_i d, 0)$, which is chosen by p_i in equilibrium. Either I generates strictly positive profits or it does not offer full insurance, as if both were false then $I = (p_i d, 0)$. Suppose I generates strictly positive profits. Then, there exists a contract $I' = (\alpha - \varepsilon, \beta)$ that, if offered exclusively to type p_i, would attract all individuals of type p_i and generate nonnegative profits. This violates the third condition for equilibrium; contradiction. Suppose now that I does not offer full insurance. Then, by Lemma 3, there exists a contract $I' = (\alpha + p_i\varepsilon, \beta - \varepsilon)$ that, if offered exclusively to type p_i, would attract all individuals of type p_i and generate nonnegative profits. This violates the third condition for equilibrium; contradiction.

Step 2. By Lemma 4, it is sufficient to show that the public premium is always actuarially unfavourable for type p_1. The public premium is determined by the balanced budget condition (1) and always actuarially unfavourable for p_1 since

$$\frac{\tau y_H}{(1-\eta)\, d} = \frac{\lambda_L p_L + \sum_{i=1}^{n} s\left(p_i\right) \lambda_i p_i}{\lambda_L \frac{y_L}{y_H} + \sum_{i=1}^{n} s\left(p_i\right) \lambda_i} > \frac{\lambda_L p_L + \left(1-\lambda_L\right) p_1}{\lambda_L \frac{y_L}{y_H} + \left(1-\lambda_L\right)} > p_1,$$

where the inequalities follow from $y_L < y_H$, $p_1 \leq p_L$, and $p_1 < p_2$. Hence, $s^*(p_1) = 0$.

Step 3. Multiple equilibria can only arise when there are two or more equilibrium strategy profiles for a given set of parameters. Suppose, by contradiction, that s^* and t^* are two equilibrium strategy profiles and $s^* \neq t^*$. By Lemma 1, we can order s^* and t^* by the lowest occurrence of a one, if any. Denote $\underline{s} = \max\{i : s^*(p_{i-1}) = 0\}$ and $\underline{t} = \max\{i : t^*(p_{i-1}) = 0\}$. Suppose, w.l.o.g., that $\underline{s} < \underline{t}$. In equilibrium, the budget balancing contribution rate that corresponds to s^* is given by

$$\tau_{\underline{s}} = (1-\eta)\, d \frac{\lambda_L p_L + \sum_{i=\underline{s}}^{n} \lambda_i p_i}{\lambda_L y_L + \sum_{i=\underline{s}}^{n} \lambda_i y_H} = (1-\eta)\, d \frac{\lambda_L p_L + \sum_{i=\underline{s}}^{\underline{t}-1} \lambda_i p_i + \sum_{i=\underline{t}}^{n} \lambda_i p_i}{\lambda_L y_L + \sum_{i=\underline{s}}^{\underline{t}-1} \lambda_i y_H + \sum_{i=\underline{t}}^{n} \lambda_i y_H}.$$

By Lemma 4, we have that $p_i \geq \tau_{\underline{s}} y_H / (1-\eta) d$ for all $i \geq \underline{s}$. Hence,

$$\tau_{\underline{s}} \quad \geq \quad (1-\eta)\, d \frac{\lambda_L p_L + \sum_{i=\underline{s}}^{\underline{t}-1} \lambda_i \frac{\tau_{\underline{s}} y_H}{(1-\eta) d} + \sum_{i=\underline{t}}^{n} \lambda_i p_i}{\lambda_L y_L + \sum_{i=\underline{s}}^{\underline{t}-1} \lambda_i y_H + \sum_{i=\underline{t}}^{n} \lambda_i y_H}.$$

Rearranging yields

$$\tau_{\underline{s}} \geq (1-\eta)\, d \frac{\lambda_L p_L + \sum_{i=\underline{t}}^n \lambda_i p_i}{\lambda_L y_L + \sum_{i=\underline{t}}^n \lambda_i y_H} = \tau_{\underline{t}}.$$

Hence, $U[(\tau_{\underline{s}} y_H, \eta), p_{\underline{s}}] \leq U[(\tau_{\underline{t}} y_H, \eta), p_{\underline{s}}]$. Further, $U[(\tau_{\underline{s}} y_H, \eta), p_{\underline{s}}] \geq U[(p_{\underline{s}} d, 0), p_{\underline{s}}]$, since $s^*(p_{\underline{s}}) = 1$, and $U[(\tau_{\underline{t}} y_H, \eta), p_{\underline{s}}] < U[(p_{\underline{s}} d, 0), p_{\underline{s}}]$, since $t^*(p_{\underline{s}}) = 0$. A contradiction:

$$U\left[(p_{\underline{s}} d, 0), p_{\underline{s}}\right] \leq U\left[(\tau_{\underline{s}} y_H, \eta), p_{\underline{s}}\right] \leq U\left[(\tau_{\underline{t}} y_H, \eta), p_{\underline{s}}\right] < U\left[(p_{\underline{s}} d, 0), p_{\underline{s}}\right].$$

The following result is used in the proof of Proposition 2.

Lemma 5. *No type chooses public insurance at actuarially unfavourable odds in the equilibrium under asymmetric information: if $s^*(p_i) = 1$, then $p_i \geq \tau y_H/(1-\eta)d$.*

Proof of Lemma 5. Suppose, by contradiction, that there exists a type p_i who chooses public insurance at actuarially unfavourable odds in the equilibrium under asymmetric information, with the equilibrium set of contracts being C^*. By Lemma 2, p_i's indifference curve through I^{pub} is steeper than those of all types $p_j > p_i$. By Lemma 2 and the continuity of $\pi(\cdot, p_i)$, there exists a contract $I = (\alpha, \beta)$, with $\alpha < \tau y_H$ and $\beta > \eta$, such that $U(I, p_i) > U(I^{pub}, p_i)$, $U(I, p_j) < U(I^{pub}, p_j) \leq \max_{I' \in C^*} U(I', p_j)$ for all $p_j > p_i$, and $\pi(I, p_i) > 0$. Since, by construction, I will only be chosen by individuals with risk p_i or lower, it will generate strictly positive profits. Since $I \notin C^*$, for if $I \in C^*$ then p_i would not choose I^{pub}, the third condition for equilibrium is violated; contradiction.

Proposition 2. *Fix a co-insurance rate η for the public plan and suppose that some high-income earners choose to remain in public insurance. The health insurance market equilibrium under asymmetric information, if it exists, can feature two scenarios:*

1. *Adverse selection: there exists a threshold type p_j, $p_1 < p_j \leq p_n$, such that $s^*(p_i) = 0$ for all $p_i < p_j$ and $s^*(p_k) = 1$ for all $p_k \geq p_j$, and the equilibrium set of contracts is*

$$C^* = \left\{ I^{pub} = \left((1-\eta)\, d \frac{\lambda_L p_L + \sum_{k=j}^n \lambda_k p_k}{\lambda_L y_L + \sum_{k=j}^n \lambda_k y_H} y, \eta \right), I^{priv} = \left(p_i (1-\beta_i)\, d, \beta_i\right)_{i \in \{i: s^*(p_i)=0\}} \right\},$$

   where $I_i^{priv} = (p_i(1-\beta_i)d, \beta_i)$ is the private contract which will be chosen by type p_i.

2. *Nonmonotone selection: there exist two threshold types, p_j and p_k, $p_1 < p_j \leq p_k < p_n$, such that $s^*(p_i) = 0$ for all $p_i < p_j$, $s^*(p_r) = 1$ for all $p_j \leq p_r \leq p_k$, and $s^*(p_l) = 0$ for all $p_l > p_k$, and the equilibrium set of contracts is*

$$C^* = \left\{ I^{pub} = \left((1-\eta)\, d \frac{\lambda_L p_L + \sum_{r=j}^k \lambda_r p_r}{\lambda_L y_L + \sum_{r=j}^k \lambda_r y_H} y, \eta \right), I^{priv} = \left(p_i (1-\beta_i)\, d, \beta_i\right)_{i \in \{i: s^*(p_i)=0\}} \right\},$$

where $I_i^{priv} = (p_i(1-\beta_i)d, \beta_i)$ is the private contract which will be chosen by type p_i.

The equilibrium schedule of private contracts satisfies the following: (i) uniqueness: I^{priv} is unique, (ii) no distortion at the top: if $s^*(p_n) = 0$, then $\beta_n = 0$, (iii) distortion at the bottom: if $s^*(p_i) = 0$ and $p_i < p_n$, then $\beta_i > 0$, (iv) incentive compatibility: if $s^*(p_i) = s^*(p_{i+1}) = 0$, then $U[(p_{i+1}(1-\beta_{i+1})d, \beta_{i+1}), p_{i+1}] = U[(p_i(1-\beta_i)d, \beta_i), p_{i+1}]$, and if $s^*(p_i) = 0$ and $s^*(p_{i+1}) = 1$, then $U(I^{pub}, p_{i+1}) = U[(p_i(1-\beta_i)d, \beta_i), p_{i+1}]$, (v) monotonicity: if $s^*(p_i) = s^*(p_j) = 0$ and $p_j > p_i$, then $\beta_j < \beta_i$, and (vi) positive insurance: if $s^*(p_i) = 0$, then $\beta_i < 1$.

Proof of Proposition 2. I proceed in a series of steps. In *Steps 1-2*, I prove the properties of the equilibrium strategy profile. In *Steps 3-10*, I prove the properties of the equilibrium private contract schedule. Finally, in *Step 11*, I provide a numerical example which shows that the two scenarios outlined in Proposition 2 can occur in an equilibrium under asymmetric information. In any case, the contribution rate for public insurance, τ, follows directly from the equilibrium strategy profile and the balanced budget condition in equation (1.1).

Step 1. I first prove that $s^*(p_1) = 0$. By Lemma 5, it suffices to show that public insurance is always actuarially unfavourable for p_1, which has been shown above.

Step 2. I now show that the types who join public insurance in equilibrium are connected, in the sense that there do not exist p_i, p_j, and p_k, $p_i < p_j < p_k$, such that $s^*(p_i) = s^*(p_k) = 1$ and $s^*(p_j) = 0$. Suppose, by contradiction, that the contrary is true. Let I be the private contract that p_j selects in equilibrium, and let W_A^I and W_{NA}^I be the final wealths corresponding to I. As I and I^{pub} are available to all types, the following three inequalities must hold:

$$p_i u\left(W_A^{pub}\right) + (1-p_i)\, u\left(W_{NA}^{pub}\right) \geq p_i u\left(W_A^I\right) + (1-p_i)\, u\left(W_{NA}^I\right). \tag{1.6}$$

$$p_j u\left(W_A^{pub}\right) + (1-p_j)\, u\left(W_{NA}^{pub}\right) < p_j u\left(W_A^I\right) + (1-p_j)\, u\left(W_{NA}^I\right). \tag{1.7}$$

$$p_k u\left(W_A^{pub}\right) + (1-p_k)\, u\left(W_A^{pub}\right) \geq p_k u\left(W_A^I\right) + (1-p_k)\, u\left(W_A^I\right). \tag{1.8}$$

Subtracting (1.6) from (1.7) and dividing by $p_j - p_i$ yields

$$u\left(W_A^{pub}\right) - u\left(W_{NA}^{pub}\right) < u\left(W_A^I\right) - u\left(W_{NA}^I\right). \tag{1.9}$$

Subtracting (1.7) from (1.8) and dividing by $p_k - p_j$ yields

$$u\left(W_A^{pub}\right) - u\left(W_{NA}^{pub}\right) > u\left(W_A^I\right) - u\left(W_{NA}^I\right);$$

contradicting (1.9). *Steps 1* and *2* together imply that only the two scenarios described in Proposition 2 are possible equilibrium strategy profiles.

Step 3. I now show that no private contract pools two or more risks in equilibrium. Suppose, by contradiction, that there exists a private contract $I = (\alpha, \beta) \in C^*$ which is chosen by a set of risks $P \subseteq \{p_1, \ldots, p_n\}$, with $|P| \geq 2$. Denote $\underline{p} = \min(P)$ and let $N = \{i : p_i \in P\}$. Since $I \in C^*$, I generates nonnegative profits:

$$\pi(I, P) = \sum_{i \in N} \lambda_i \left[\alpha - p_i (1 - \beta) d\right] \geq 0.$$

Solving for α and noting that $|P| \geq 2$, we have that:

$$\pi\left(I, \underline{p}\right) = \alpha - \underline{p}(1-\beta)d \geq (1-\beta)d\left(\frac{\sum_{i \in N}\lambda_i p_i}{\sum_{i \in N}\lambda_i} - \underline{p}\right) > (1-\beta)d\left(\underline{p}\frac{\sum_{i \in N}\lambda_i}{\sum_{i \in N}\lambda_i} - \underline{p}\right) = 0.$$

That is, I generates strictly positive profits if sold exclusively to type $\underline{p}$. By Lemma 2, $\underline{p}$'s indifference curve through I is steeper than those of all types in the set $P \setminus \{\underline{p}\}$. Thus by Lemma 2 and the continuity of $\pi(\cdot, \underline{p})$, there exists a contract $I' = (\alpha', \beta')$, with $\alpha' < \alpha$ and $\beta' > \beta$, such that $U(I', \underline{p}) > U(I, \underline{p})$, $U(I', p_i) < U(I, p_i)$ for all $p_i \in P \setminus \{\underline{p}\}$, and $\pi(I', \underline{p}) > 0$. Since $I' \notin C^*$, for if $I' \in C^*$ then $\underline{p}$ would not choose I, the third condition for equilibrium is violated; contradiction.

Step 4. I now show that no private contract generates strictly positive profits in equilibrium. Suppose, by contradiction, that there exists a contract $I = (\alpha, \beta) \in C^*$ which generates strictly positive profits. By Step 3 and the definition of C^*, I must be chosen by one and only one type. Let this type be p_i. By Lemma 2 and the continuity of $\pi(\cdot, p_i)$, there exists a contract $I' = (\alpha', \beta')$, with $\alpha' < \alpha$ and $\beta' > \beta$, such that $U(I', p_i) > U(I, p_i)$, $U(I', p_j) < U(I, p_j) \leq \max_{I'' \in C^*} U(I'', p_j)$ for all $p_j > p_i$, and $\pi(I', p_i) > 0$. Since $I' \notin C^*$, for if $I' \in C^*$ then p_i would not choose I, the third condition for equilibrium is violated; contradiction. This implies that the private equilibrium contracts are of the form $I_i^{priv} = (p_i(1-\beta_i)d, \beta_i)$.

Step 5. To show that there is no distortion at the top, suppose, by contradiction, that $s^*(p_n) = 0$ and $I_n^{priv} = (p_n(1-\beta_n)d, \beta_n)$ with $\beta_n > 0$. Because of Lemma 3, any contract $I' = (p_n(1-\beta_n')d, \beta_n')$ with $\beta_n' < \beta_n$ guarantees that $U(I', p_n) > U(I_n^{priv}, p_n)$. The contract I', if offered, will be chosen by consumers with risk p_n or lower, thus generating nonnegative profits. This violates the third condition for equilibrium; contradiction.

Step 6. To show that there is distortion at the bottom, suppose, by contradiction, that $s^*(p_i) = 0$ for some $p_i < p_n$ and $I_i^{priv} = (p_i d, 0)$. Consider the type p_n. Either $s^*(p_n) = 0$ or $s^*(p_n) = 1$. Suppose the former is true. We know, by *Step 5*, that $I_n^{priv} = (p_n d, 0)$, implying that $U(I_n^{priv}, p_n) < U(I_i^{priv}, p_n)$. Hence, the contract intended for p_i will also be chosen by p_n. Since all contracts must be separating (*Step 3*), this leads to a contradiction. Suppose now that $s^*(p_n) = 1$. In this case, we must have that $U(I^{pub}, p_n) \geq u(y_H - p_i d)$. We must also have that $U(I^{pub}, p_i) < u(y_H - p_i d)$, since $s^*(p_i) = 0$. But since $p_i < p_n$, $U(I^{pub}, p_i) > U(I^{pub}, p_n)$, contradicting the two preceding inequalities.

Step 7. Before I show that incentive compatibility has to hold with equality, note that local incentive compatibility (IC) constraints are necessary, since contracts have to be separating, and sufficient, since expected utility satisfies the Spence-Mirrlees strict single crossing property. Suppose now, by contradiction, that some local IC constraint is not binding, i.e., $\max_{I \in C^*} U(I, p_{i+1}) > U(I_i^{priv}, p_{i+1})$ for some p_i such that $s^*(p_i) = 0$, where $I_i^{priv} = (p_i(1-\beta_i)d, \beta_i)$. Either $s^*(p_{i+1}) = 0$ or $s^*(p_{i+1}) = 1$. Suppose the former is true. Then, $U(I_{i+1}^{priv}, p_{i+1}) > U(I_i^{priv}, p_{i+1})$, where $I_{i+1}^{priv} = (p_{i+1}(1-\beta_{i+1})d, \beta_{i+1})$ by the preceding steps. By Lemma 3 and the continuity of $U(\cdot, p_{i+1})$, there exists a contract $I' = (p_i(1-\beta_i')d, \beta_i')$, with $\beta_i' < \beta_i$, such that $U(I_{i+1}^{priv}, p_{i+1}) > U(I', p_{i+1})$ and $U(I', p_i) > U(I_i^{priv}, p_i)$. The contract I', if offered, will be chosen by consumers with risk p_i or lower and generate nonnegative profits. This violates the third condition for equilibrium; contradiction. Suppose now that $s^*(p_{i+1}) = 1$. Then, $U(I^{pub}, p_{i+1}) > U(I_i^{priv}, p_{i+1})$. By Lemma 3 and the continuity of $U(\cdot, p_{i+1})$, there exists a contract $I' = (p_i(1-\beta_i')d, \beta_i')$, with $\beta_i' < \beta_i$, such that $U(I^{pub}, p_{i+1}) > U(I', p_{i+1})$ and $U(I', p_i) > U(I_i^{priv}, p_i)$. The contract I', if offered, will be chosen by consumers with risk p_i or lower and generate nonnegative profits. This violates the third condition for equilibrium; contradiction.

Step 8. To show that monotonicity has to hold, suppose, by contradiction, that $s^*(p_i) = s^*(p_j) = 0$ for some $p_j > p_i$, and $\beta_j \geq \beta_i$. We have that

$$\begin{aligned}
U\left[\left(p_i\left(1-\beta_i\right)d, \beta_i\right), p_j\right] &= p_j u\left[y_H - \beta_i d - p_i\left(1-\beta_i\right)d\right] + \left(1-p_j\right)u\left[y_H - p_i\left(1-\beta_i\right)d\right] \\
&> p_j u\left[y_H - \beta_i d - p_j\left(1-\beta_i\right)d\right] + \left(1-p_j\right)u\left[y_H - p_j\left(1-\beta_i\right)d\right] \\
&\geq p_j u\left[y_H - \beta_j d - p_j\left(1-\beta_j\right)d\right] + \left(1-p_j\right)u\left[y_H - p_j\left(1-\beta_j\right)d\right] \\
&= U\left[\left(p_j\left(1-\beta_j\right)d, \beta_j\right), p_j\right],
\end{aligned}$$

where the first inequality follows from $p_j > p_i$ and the second inequality follows from $\beta_j \geq \beta_i$ and Lemma 3. This violates incentive compatibility; contradiction.

Step 9. Uniqueness of the private contract schedule follows from the fact that $U[(p_i(1-\beta_i)d, \beta_i), p_{i+1}]$ is strictly decreasing in β_i, as shown in Lemma 3, so that there is exactly one β_i such that incentive compatibility is satisfied with equality.

Step 10. I now show that every private contract which is chosen in equilibrium entails positive insurance. Suppose, by contradiction, that $s^*(p_i) = 0$ and $\beta_i = 1$ for some $p_i < p_n$ (remember that $\beta_n = 0$). Either $s^*(p_{i+1}) = 0$ or $s^*(p_{i+1}) = 1$. Suppose the former is true. It follows from *Step 8* that $\beta_{i+1} < 1$. But then,

$$\begin{aligned}
& U\left[\left(p_{i+1}\left(1-\beta_{i+1}\right)d, \beta_{i+1}\right), p_{i+1}\right] \\
=\; & p_{i+1} u\left[y_H - \beta_{i+1} d - p_{i+1}\left(1-\beta_{i+1}\right)d\right] + \left(1-p_{i+1}\right)u\left(y_H - p_{i+1}\left(1-\beta_{i+1}\right)d\right) \\
>\; & p_{i+1} u\left(y_H - d\right) + \left(1-p_{i+1}\right)u\left(y_H\right) = U\left[\left(p_i\left(1-\beta_i\right)d, \beta_i\right), p_{i+1}\right],
\end{aligned}$$

where the inequality follows from Lemma 3. This violates the requirement that incentive compatibility has to be satisfied with equality; contradiction.

Suppose now that $s^*(p_{i+1}) = 1$. If $\eta = 1$, then a contradiction follows immediately, since $s^*(p_i) = 0$ requires that $U(I^{pub}, p_i) < U[(p_i(1-\beta_i)d, \beta_i), p_i]$, but $I^{pub} = (p_i(1-\beta_i)d, \beta_i) = (0, 1)$. If $\eta < 1$, then

$$\begin{aligned} U\left(I^{pub}, p_{i+1}\right) &= U\left[\left(\tau y_H, \eta\right), p_{i+1}\right] \\ &\geq U\left[\left(p_{i+1}(1-\eta)d, \eta\right), p_{i+1}\right] \\ &> U\left[\left(p_i(1-\eta)d, \eta\right), p_{i+1}\right] \\ &> U\left[\left(0, 1\right), p_{i+1}\right] \\ &= U\left[\left(p_i(1-\beta_i)d, \beta_i\right), p_{i+1}\right], \end{aligned}$$

where the first and third inequality follow from Lemma 5 and Lemma 3, respectively. This violates the requirement that incentive compatibility has to be satisfied with equality; contradiction.

Step 11. Suppose there are three types and $u(x) = \ln(x)$. Let the parameters be those reported in Table 1.5. The co-insurance rate under public insurance, η, is left undetermined.

Table 1.5: Parameterisation

Population shares		Risks		Incomes & loss	
λ_L	0.6	p_L	0.35	y_H	1
λ_1	0.05	p_1	0.3	y_L	0.9
λ_2	0.1	p_2	0.5	d	0.8
λ_3	0.25	p_3	0.6		

Consider first the private sector in isolation. The three candidate-to-equilibrium contracts are $I_3^{priv} = (0.48, 0)$, $I_2^{priv} = (0.4(1-\beta_2), \beta_2)$, and $I_1^{priv} = (0.24(1-\beta_1), \beta_1)$, where β_1 and β_2 satisfy the following two incentive-compatibility constraints:

$$U\left(I_3^{priv}, p_3\right) = U\left(I_2^{priv}, p_3\right). \tag{1.10}$$

$$U\left(I_2^{priv}, p_2\right) = U\left(I_1^{priv}, p_2\right). \tag{1.11}$$

(1.10) and (1.11) are jointly satisfied for $\beta_2 \approx 0.5361$ and $\beta_1 \approx 0.7625$. It can easily be shown that there does not exist a pooling contract which can break the separating equilibrium, i.e., a private sector equilibrium exists.

Now focus on the public plan. In equilibrium, the contribution rate must satisfy

$$\tau = (1-\eta)\, 0.8 \frac{0.6 \cdot 0.35 + 0.05 \cdot 0.3 s^*\left(p_1\right) + 0.1 \cdot 0.5 s^*\left(p_2\right) + 0.25 \cdot 0.6 s^*\left(p_3\right)}{0.6 \cdot 0.9 + 0.05 s^*\left(p_1\right) + 0.1 s^*\left(p_2\right) + 0.25 s^*\left(p_3\right)}.$$

Consider an equilibrium with adverse selection in which the high and medium risks join public insurance and the low risks purchase private insurance: $s^*(p_1) = 0$, $s^*(p_2) = s^*(p_3) = 1$. In this case, it must be that $\tau = 164(1-\eta)/445$. If $\tau = 164(1-\eta)/445$, then $s^*(p_2) = s^*(p_3) = 1$ if and only if the following two inequalities are satisfied:

$$U\left(I_3^{priv}, p_3\right) \leq 0.6 \ln\left[1 - 0.8\eta - \frac{164}{445}(1-\eta)\right] + 0.4 \ln\left[1 - \frac{164}{445}(1-\eta)\right].$$
$$U\left(I_2^{priv}, p_2\right) \leq 0.5 \ln\left[1 - 0.8\eta - \frac{164}{445}(1-\eta)\right] + 0.5 \ln\left[1 - \frac{164}{445}(1-\eta)\right].$$

The two inequalities are satisfied if $\eta \leq 0.5956$. Given that $s^*(p_2) = 1$, the incentive compatibility constraint that determines $I_1^{priv} = (0.24(1-\beta_1), \beta_1)$ is now given by

$$U\left(I_1^{priv}, p_2\right) = 0.5 \ln\left[1 - 0.8\eta - \frac{164}{445}(1-\eta)\right] + 0.5 \ln\left[1 - \frac{164}{445}(1-\eta)\right].$$

Solving, we obtain that $\beta_1 = \beta_1(\eta) = (5\sqrt{165312\eta^2 + 41307\eta + 300325} - 1691)/1869$, which is increasing in η. In conclusion, for $\eta \leq 0.5956$, there exists an equilibrium with $s^*(p_1) = 0$, $s^*(p_2) = 1$, and $s^*(p_3) = 1$. The corresponding equilibrium set of contracts is $C^* = \{I^{pub} = (164(1-\eta)y/445, \eta), I_1^{priv} = (0.24(1-\beta_1(\eta)), \beta_1(\eta))\}$.

Now consider the unique equilibrium scenario with nonmonotone selection, in which the medium risks join public insurance and the low and high risks join private insurance: $s^*(p_1) = s^*(p_3) = 0$, $s^*(p_2) = 1$. In this case, it must be that $\tau = 0.325\,(1-\eta)$. If $\tau = 0.325(1-\eta)$, then $s^*(p_3) = 0$ and $s^*(p_2) = 1$ if and only if the following two inequalities are satisfied:

$$U\left(I_3^{priv}, p_3\right) > 0.6 \ln\left[1 - 0.8\eta - 0.325\,(1-\eta)\right] + 0.4 \ln\left[1 - 0.325\,(1-\eta)\right].$$
$$U\left(I_2^{priv}, p_2\right) \leq 0.5 \ln\left[1 - 0.8\eta - 0.325\,(1-\eta)\right] + 0.5 \ln\left[1 - 0.325\,(1-\eta)\right].$$

The two inequalities are satisfied if $0.6547 \leq \eta \leq 0.6844$. The private contract which is intended for p_1 is given by $I_1^{priv} = (0.24(1-\beta_1(\eta)), \beta_1(\eta))$, where $\beta_1(\eta) = (5\sqrt{5187\eta^2 + 3402\eta + 7795} - 304)/336$ solves $U(I_1^{priv}, p_2) = 0.5\ln[1 - 0.8\eta - 0.325(1-\eta)] + 0.5\ln[1 - 0.325(1-\eta)]$. In conclusion, for $0.6547 \leq \eta \leq 0.6844$, there exists an equilibrium with $s^*(p_1) = 0$, $s^*(p_3) = 0$, and $s^*(p_2) = 1$. The corresponding equilibrium set of contracts is given by $C^* = \{I^{pub} = (0.325(1-\eta)y, \eta), I_1^{priv} = (0.24(1-\beta_1(\eta)), \beta_1(\eta)), I_3^{priv} = (0.48, 0)\}$. Note that public insurance is advantageously selected in this case, given that $\mathbb{E}_p[pd \mid s^*(p) = 1] = 0.5 < 0.5375 = \mathbb{E}_p[pd]$.

It can moreover be shown that there is a unique equilibrium with $s^* = 0$ whenever $\eta \geq 0.7009$.

1.B Robustness Checks

1.B.1 Magnitude of Selection

Table 1.6: Robustness checks: Magnitude of selection

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No controls						
$\hat{\rho}$	-0.152***	-0.169***	-0.108***	-0.173***	-0.144***	-0.150**
Wald test of $\rho = 0$ (p-value)	(0.008)	(0.008)	(0.004)	(0.000)	(0.002)	(0.013)
Panel B: Control for observables						
$\hat{\rho}$	-0.079	-0.098	-0.046	-0.131**	-0.102*	-0.109
Wald test of $\rho = 0$ (p-value)	(0.235)	(0.167)	(0.291)	(0.020)	(0.062)	(0.118)
N	8,366	6,681	11,892	12,787	10,677	4,741

Notes: Table reports the correlation of the residuals from bivariate probit estimations of equations (1.2) and (1.3). Panel A reports the correlations for the model with $b = c = 0$. Panel B reports the correlations for the model with $c = 0$. Column 1 shows estimates after controlling for a summary indicator of chronic conditions, body mass index, and physical and mental component scales. Column 2 shows estimates after controlling for indicators for 9 chronic conditions, body mass index, and physical and mental component scales. The dependent variable HOSPITAL in column 3 is an indicator which equals one if an individual is hospitalised in period $t+1$ or $t+2$. The dependent variable HOSPITAL in column 4 is an indicator which equals one if an individual stays 3 or more nights in the hospital in period $t+1$. Column 5 shows estimates after excluding individuals with zero income (civil servants and the self-employed) and restricts the income sample to those individuals with more than 5,000 Euros above the *compulsory insurance threshold.* Column 6 shows estimates for the subsample of individuals who are in the first or second year of being eligible to choose private insurance. Standard errors adjusted for clustering at the individual level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

1.B.2 Sources of Selection

Table 1.7: Robustness checks: Sources of selection

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: OPTOUT						
Self-assessed health	0.005	0.005	0.003	0.003	0.003	0.005
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.005)
Risk aversion	-0.002	-0.003	-0.002*	-0.003**	-0.003**	-0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
West Germany	-0.031***	-0.025***	-0.025***	-0.025***	-0.027***	-0.044***
	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)	(0.009)
Dependent variable: HOSPITAL						
Self-assessed health	-0.022***	-0.024***	-0.042***	-0.026***	-0.028***	-0.016**
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)
Risk aversion	-0.004*	-0.006**	-0.005*	-0.003*	-0.004*	-0.006*
	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
West Germany	-0.005	-0.006	-0.013	-0.014*	-0.010	0.004
	(0.008)	(0.008)	(0.011)	(0.006)	(0.007)	(0.010)
N	8,193	6,676	11,381	12,019	10,048	4,189

Notes: Table reports average marginal effects of the unused observables from bivariate probit estimations of equations (1.2) and (1.3). Column 1 shows estimates after controlling for a summary indicator of chronic conditions, body mass index, and physical and mental component scales. Column 2 shows estimates after controlling for indicators for 9 chronic conditions, body mass index, and physical and mental component scales. The dependent variable HOSPITAL in column 3 is an indicator which equals one if an individual is hospitalised in period $t+1$ or $t+2$. The dependent variable HOSPITAL in column 4 is an indicator which equals one if an individual stays 3 or more nights in the hospital in period $t+1$. Column 5 shows estimates after excluding individuals with zero income (civil servants and self-employed) and restricts the income sample to those individuals with more than 5,000 Euros above the *compulsory insurance threshold.* Column 6 shows estimates for the subsample of individuals who are in the first or second year of being eligible to choose private insurance. Means of OPTOUT and HOSPITAL vary across columns. Standard errors adjusted for clustering at the individual level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

1.B.3 Testing for Asymmetric Information

Table 1.8: Robustness checks: Testing for asymmetric information

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: OPTOUT						
SAH=1	0.021	0.018	0.016	0.010	0.011	0.010
	(0.027)	(0.033)	(0.021)	(0.018)	(0.020)	(0.039)
SAH=2 (omitted)	0.000	0.000	0.000	0.000	0.000	0.000
	—	—	—	—	—	—
SAH=3	0.009	0.017*	0.012	0.014*	0.016*	0.032**
	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)	(0.012)
SAH=4	0.013	0.016*	0.012*	0.014**	0.014*	0.035**
	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)	(0.011)
SAH=5	0.023*	0.028**	0.016*	0.022**	0.023**	0.041**
	(0.010)	(0.011)	(0.007)	(0.007)	(0.008)	(0.014)
Dependent variable: HOSPITAL						
SAH=1	0.012	0.074	0.057	0.062	0.064	0.017
	(0.037)	(0.068)	(0.043)	(0.032)	(0.037)	(0.048)
SAH=2 (omitted)	0.000	0.000	0.000	0.000	0.000	0.000
	—	—	—	—	—	—
SAH=3	-0.048***	-0.049**	-0.063***	-0.039***	-0.035**	-0.032*
	(0.014)	(0.017)	(0.016)	(0.011)	(0.012)	(0.016)
SAH=4	-0.071***	-0.070***	-0.107***	-0.063***	-0.068***	-0.043**
	(0.016)	(0.018)	(0.016)	(0.010)	(0.012)	(0.016)
SAH=5	-0.072***	-0.073***	-0.125***	-0.072***	-0.076***	-0.053**
	(0.018)	(0.021)	(0.019)	(0.012)	(0.014)	(0.018)
N	8,363	6,676	11,820	12,777	10,668	4,737

Notes: Table reports average marginal effects of the five categories of self-assessed health from bivariate probit estimations of equations (1.2) and (1.3). 1=very bad, 2=bad, 3=satisfactory, 4=good, 5=very good. Column 1 shows estimates after controlling for a summary indicator of chronic conditions, body mass index, and physical and mental component scales. Column 2 shows estimates after controlling for indicators for 9 chronic conditions, body mass index, and physical and mental component scales. The dependent variable HOSPITAL in column 3 is an indicator which equals one if an individual is hospitalised in period $t+1$ or $t+2$. The dependent variable HOSPITAL in column 4 is an indicator which equals one if an individual stays 3 or more nights in the hospital in period $t+1$. Column 5 shows estimates after excluding individuals with zero income (civil servants and self-employed) and restricts the income sample to those individuals with more than 5,000 Euros above the *compulsory insurance threshold.* Column 6 shows estimates for the subsample of individuals who are in the first or second year of being eligible to choose private insurance. Means of OPTOUT and HOSPITAL vary across columns. Standard errors adjusted for clustering at the individual level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

2 Do Doctors Prescribe Antibiotics Out of Fear of Malpractice?

2.1 Introduction

Doctors in the U.S. (and elsewhere) prescribe too many antibiotics. According to recent estimates, up to 50% of antibiotics prescribed in the ambulatory care setting are inappropriate (CDC 2013). The misuse of antibiotics promotes the growth of antibiotic resistance, which is one of the most pressing public health issues that many developed countries face today. Worldwide, at least 700,000 patients die every year because of antibiotic resistance, and many more become infected with antibiotic-resistant bacteria (O'Neill 2014). In light of this, the question becomes, why do doctors prescribe unnecessary antibiotics?

A possible explanation for why U.S. doctors prescribe so many antibiotics lies in the medical malpractice system. Doctors in the U.S. face considerable liability pressure as about one in 14 is sued in every given year (Jena *et al.* 2011). In response to this pressure, doctors have been found to resort to defensive medicine, that is, to administer tests, treatments, or medications with expected benefits below cost in order to protect themselves against potential legal proceedings (see the review by Kessler *et al.* 2006). The frequent use of antibiotics may constitute a form of defensive medicine: doctors may feel inclined to prescribe an antibiotic against their own clinical judgement because the antibiotic presents a safeguard against serious bacterial infections, which may trigger a malpractice claim if left untreated. Anecdotal evidence and physician surveys support this theory,[17] but, to date, no attempt has been made to examine whether liability pressure plays a role in actual clinical decisions to prescribe antibiotics.

This paper is the first to systematically analyze the impact of liability pressure on antibiotic prescriptions. I begin by constructing a stylized model of antibiotic prescribing under the threat of malpractice. Based on patient symptoms, a physician has to decide whether or not to prescribe an antibiotic, taking into account the patient's expected utility; expected medical liability costs; and the external cost of increased antibiotic resistance. The model shows that an increase in liability pressure can lead to an increase or decrease in antibiotic prescriptions, depending on how much of a bias the tort law introduces towards (or against, for that matter) prescribing antibiotics relative to what the physician would choose in its absence. Given that two arguably realistic assumptions are satisfied, the model says that direction of the change in antibiotic prescriptions after a change in liability pressure is informative of the social wastefulness of these antibiotics. As such, the model gives rise to a test of defensive

[17] For instance, of the 669 physicians who participated in a survey in Pennsylvania, 33% reported that they frequently prescribe more medication than medically indicated in response to liability pressure, and an additional 36% reported that they occasionally prescribe medication to avoid potential litigation (Studdert *et al.* 2005).

medicine whose only requirement is an estimate of the causal effect of liability pressure on antibiotic prescriptions.

Using data from the National Ambulatory Medical Care Survey (NAMCS), a nationally representative sample of visits to office-based physicians in the U.S., I estimate the causal effect of liability pressure on antibiotic prescriptions with a difference-in-differences design based on the variation in tort reforms across U.S. states from 1993 to 2011. I allow for heterogenous responses to reforms across doctors and patients, for example, based on the patient's type of health insurance or the physician's specialty. Throughout the analysis, I carefully consider the possibility that preexisting trends in the medical care sector cause tort reforms and not vice versa.

Results show that doctors respond to liability pressure by prescribing more antibiotics. After the introduction of a cap on noneconomic damages – a commonly adopted tort reform that reduces the liability pressure on physicians – doctors are about 6 percent less likely to prescribe antibiotics. Extrapolating to the U.S. population, I estimate that, per year, there would be 3.2 million fewer ambulatory care visits in which doctors prescribe antibiotics if all states adopted caps on noneconomic damages. Results also show that doctors do not prescribe less drugs per patient visit, suggesting that doctors substitute other drugs for antibiotics when they face less liability pressure. Indeed, I find that doctors prescribe more antitussives – a form of cough medication that often represents a more effective treatment than antibiotics in cases of upper respiratory tract infections – after the enactment of noneconomic damages caps. With regard to potential heterogeneous effects of noneconomic damages cap reforms, I find that patients aged 65 and above are not affected by noneconomic damages caps. This can be explained by the fact that older patients pose less of a malpractice risk to physicians because of lower future earnings losses. Other factors that have previously been identified to lead to heterogeneous responses to tort reforms – such as patients being insured by Medicaid, the physician's specialty, and HMO ownership of the practice – do not play a role in determining antibiotic prescriptions after noneconomic damages cap reforms.

Adopting the same difference-in-differences strategy as described above but using data from the Nationwide Inpatient Sample (NIS), I investigate whether noneconomic damages cap reforms lead to a change in hospital stays for conditions that can be prevented through the timely use of antibiotics. Following the medical literature, I focus on the following six health outcomes that can be linked to antibiotic use in the outpatient setting: peritonsillar abscess, rheumatic fever, mastoiditis, septicemia, pneumonia, and meningitis. By and large, the empirical evidence indicates that noneconomic damages caps do not affect hospital discharges for such conditions.

Taken together, the empirical results, as well as the theoretical model, suggest that liability pressure induces physicians to prescribe antibiotics that have no clear health benefits, or in other words, that physicians use antibiotics as defensive medicine. While the monetary cost of defensive medication treatments may be small compared to other cases of defensive medicine (after all, antibiotics are relatively cheap), there is also the indirect cost tied to increased antibiotic resistance. In this regard, antibiotics are a particularly alarming case of defensive medicine, given that defensively used antibiotics do not only constitute a waste of resources but also negatively affect the health of others due to their external effect on antibiotic resistance.

The rest of this paper is structured as follows. Section 2.2 provides background information and references to the relevant literatures. Section 2.3 presents the theory. Section 2.4 describes the data and provides summary statistics. Section 2.5 explains the empirical strategy. Section 2.6 presents the empirical results. Section 2.7 concludes.

2.2 Background

2.2.1 Antibiotic Resistance

Antibiotics are used to treat bacterial infections and represent one of the most important tools in modern medicine. Antibiotics are essential for many medical procedures, including chemotherapy, dialysis, Cesarean sections, and organ transplants, because of their ability to prevent infectious complications in vulnerable patients. Antibiotics are also used in the husbandry of livestock, partially, to promote the growth of animals; a practice that has recently come under scrutiny.

The efficacy of antibiotics cannot be taken for granted. Bacteria evolve and develop mechanisms to resist the antibiotics that are used to combat them. Over the course of the last 20 years, antibiotic resistance has become an increasingly alarming issue due to the combination of two major factors: a sharp increase in antibiotic consumption and a shortage of new antibiotics to replace those which have become ineffective. Today, it is estimated that over 2 million U.S. residents acquire antibiotic-resistant infections in a given year, and that these infections result in more than 23,000 annual deaths (CDC 2013). Mortality from MRSA (methicillin-resistant Staphylococcus aureus), which is just one of many microorganisms that have developed resistance to antibiotics, exceeds mortality due to asthma, homicide, or HIV/AIDS (Klevens *et al.* 2007, CDC 2015). The economic impact of antibiotic resistance, while difficult to measure, is likely to be huge: estimates of the cost of antibiotic resistance range from 55 billion USD per year for the U.S. economy alone to 100 trillion USD for the world economy until 2050 (CDC 2013, O'Neill 2014). In response to this growing problem, many influential institutions, among them the World Health Organization and the Centers for Disease Control and Prevention, have issued reports and called for action to combat the rise in antibiotic resistance (WHO 2014, CDC 2013).

Any use of antibiotics, no matter how conservative and appropriate, contributes to the development of resistant bacteria. But, the widespread misuse of antibiotics that we observe in practice, for example for acute respiratory tract infections such as the common cold, makes the problem worse. For the U.S., which is among the countries with the highest per capita consumption of antibiotics in the world (Van Boeckel *et al.* 2014), it is estimated that between 25 and 50% of all antibiotics are prescribed unnecessarily (CDC 2013, Shapiro *et al.* 2014).[18] Furthermore, there exist large differences in antibiotic usage across U.S. states, with some states prescribing twice as many antibiotics on a per capita basis as others (Hicks *et al.* 2013). Finally, even if antibiotics are indicated for treatment, physicians often prescribe non-recommended broad-spectrum antibiotics, which contribute more to the growth in antibiotic resistance, instead of relying on equally effective (and cheaper) narrow-spectrum antibiotics (Linder and Stafford 2001).

The question is, why do physicians prescribe so many antibiotics? Prior research has shown that physicians prescribe more antibiotics if they can benefit financially from prescribing (Currie *et al.* 2014), patient expectations play an important role (Mangione-Smith *et al.* 1999), peer effects matter (Kwon and Jun 2015), and provider competition can encourage antibiotic use (Fogelberg 2014). One lesson that can be drawn from these findings from different countries is that physicians are influenced by the institutional setup of the healthcare system they practice in. Physicians who practice in the U.S. generally invoke three reasons why they prescribe antibiotics that may not be clinically indicated: patient pressure, to end the visit rapidly, and to avoid potential litigation (Bauchner *et al.* 1999). The latter reason is the focus of this study and will be discussed in more detail in the following sections.

2.2.2 Liability for Medical Malpractice and Defensive Medicine

In most countries around the world, patients can sue the attending physician when they suffer harm. In the U.S., liability for medical malpractice is generally based on the negligence standard. To prove a case of medical malpractice, a plaintiff must establish that: (1) the care that he or she received fell below the standard of care that is expected from physicians in the community, (2) the care that he or she received was performed negligently, and (3) there is a causal connection between the injury that he or she suffers from and the care that the physician provided.

Even though many adverse events that are caused by medical negligence do not result in the patient filing a malpractice claim (Localio *et al.* 1991), physicians in the U.S. still have to defend a large amount of claims each year. Jena *et al.* (2011) estimate that 7.4% of all physicians are sued in a given year, and that the lifetime risk of being sued ranges between 75% and 99%, depending on physician specialty. Defending a malpractice claim is costly for physicians mainly because there are large nonmonetary costs that are associated with being

[18] On top of promoting the growth of antibiotic resistance, inappropriately prescribed antibiotics directly cost the U.S. healthcare system more than $1.1 billion per year (Fendrick *et al.* 2003) and lead to a myriad of preventable adverse drug reactions (CDC 2013).

sued, two of which are particularly important. First, physicians have to devote a considerable amount of time to defending malpractice claims. Seabury *et al.* (2013) show that the average physician spends more than four years with an unresolved malpractice claim, and Studdert *et al.* (2006) report that the average time between injury and closure of a claim is five years. Second, a malpractice incidence can severely damage a physician's reputation, and as Dranove *et al.* (2012) have shown, such reputational damages are associated with economically significant costs. Direct monetary costs arise relatively seldom from a malpractice claim, as most physicians are fully insured against malpractice risks (Danzon 2000, Zeiler *et al.* 2007). For this reason, physicians should care more about the probability of being sued than awards.

One goal of liability for medical malpractice is to align the interests of physicians and other healthcare providers with those of patients: by punishing healthcare professionals for providing too little care, liability is supposed to reduce adverse health outcomes. However, as we know since at least from Kessler and McClellan (1996), liability can also induce physicians to provide too much care. This is referred to as defensive medicine, which, in the economics literature, is defined as care that physicians order to avoid lawsuits but for which cost exceeds expected benefits. The empirical evidence suggests that physicians practice defensive medicine by increasing treatment intensity for heart attack patients (Kessler and McClellan 1996, Avraham and Schanzenbach 2015) and ordering more imaging services (Baicker *et al.* 2007). The evidence regarding the rates of Cesarean sections, whose excessive use is often attributed to liability pressure, is less conclusive: while Dubay *et al.* (1999) and Shurtz (2013) find that physicians perform more Cesarean sections following an increase in liability pressure, Currie and MacLeod (2008) and Amaral-Garcia *et al.* (2015) find the opposite.

Whether physicians prescribe medication to protect themselves against potential malpractice claims has not yet been investigated in actual clinical situations. Errors of medication are a common cause of medical misadventures and often lead to malpractice claims (Leape *et al.* 1991, Rothschild *et al.* 2002). Not surprisingly therefore, two questionnaire surveys suggest that about a third of physicians regularly prescribe more medication in response to liability pressure (Summerton 1995, Studdert *et al.* 2006). In the context of antibiotics, it is clear that not prescribing an antibiotic to a patient with a bacterial infection can trigger a malpractice claim against the physician, for example when the patient suffers from pneumonia or meningitis.[19] Adding to this, it is often difficult for physicians to differentially diagnose between conditions that require an antibiotic and those that do not (Coenen *et al.* 2000). As antibiotics are relatively safe and inexpensive, physicians may be inclined to prescribe them in marginal cases and even when an antibiotic is not clinically indicated. However, prescribing antibiotics bears the risk of adverse drug reactions, which may as well lead to a malpractice

[19]There exist numerous examples of malpractice claims in which patients sue their physician for delaying or denying antibiotic treatment; see, for example, *Pasquale v. Miller* (1993), *Gartner v. Hemmer* (2002), and *Burgess v. Mt. Vernon Developmental Center* (2009). Moreover, by prescribing an antibiotic, physicians can also hope to avoid malpractice claims which are based on a failure to diagnose a bacterial infection.

claim. Hence, when it is clear that the patient does not require an antibiotic, physicians are better off not prescribing one when they want to minimize the risk of litigation.

Another open question is whether liability pressure affects the type of antibiotics that physicians prescribe. One may expect that physicians who are worried about potential malpractice claims prescribe relatively more broad-spectrum antibiotics, given that these act against a wider range of bacteria than narrow-spectrum antibiotics.[20] On the other hand, physicians may also prefer to prescribe narrow-spectrum to the marginal patient given that narrow-spectrum antibiotics are cheaper, generally cause less side effects, and contribute less to the growth in antibiotic resistance than broad-spectrum antibiotics.

2.2.3 Tort Reform

The terms on which patients in the U.S. can sue their physician are determined by the tort law, which differs across states. Spurred in part by three major medical malpractice crises (in the 1970s, 1980s, and 2000s), most states have reformed their tort laws to keep malpractice insurance from becoming unaffordable and to mitigate the liability pressure on physicians. The following four are the most commonly adopted reforms over the period from 1993 to 2011.

1. Caps on noneconomic damages: Noneconomic damages are awarded for nonpecuniary harms, such as pain and suffering, loss of consortium, and emotional distress. They account for about 50% of the typical medical malpractice award (Hyman *et al.* 2009) and are often controversial, given that nonmonetary losses are inherently hard to quantify. Following the example of California, which introduced a cap of $250,000 in 1975, the majority of states have now adopted caps on noneconomic damages.

2. Caps on punitive damages: Punitive damages are designed to punish tortfeasors and deter misconduct. As they are usually restricted to cases that involve intent, actual malice, or gross negligence, punitive damages are awarded relatively infrequently in medical malpractice cases. Many states cap the amount of punitive damages that can be awarded, where the cap can be a fixed amount, a ratio between punitive damages and compensatory damages that cannot be exceed, an amount that is determined by the defendant's net worth or income, or a combination thereof. Some states, such as Michigan, do not allow for punitive damages unless they are specifically provided by statute, and other states, such as Nebraska, impose an outright ban on punitive damages.

3. Modifications of the collateral-source rule (CSR): The common law CSR prohibits the admission of evidence that the plaintiff has been compensated for his or her losses from

[20] For example, in *McIntiry v. Stubbs* (1983), the physician prescribed narrow-spectrum antibiotics, which did not cure the patient's meningitis, and was sued for failing to prescribe broad-spectrum antibiotics.

sources other than the defendant, such as the plaintiff's health insurance. Tort reform advocates argue that the rule allows plaintiff to be compensated twice for the same injury and lobby for its abrogation. In fact, the majority of states have now altered or abolished the common law CSR.

4. Modifications of the joint-and-several liability (JSL) rule: Under the common law JSL rule, plaintiffs can recover damages from multiple defendants collectively or from each defendant individually, regardless of the shares of liability that are apportioned to the defendants. If a plaintiff recovers all damages from one defendant, it is then up to this defendant to pursue the other defendants to contribute for their respective shares of the liability. More than two-thirds of states have limited the application of JSL or replaced it with the proportionate liability rule, under which defendants cannot be asked to pay for more than what they are responsible for.

A large body of research investigates the effect of tort reforms on the medical malpractice environment.[21] The conclusion that has emerged from this literature is that caps on noneconomic damages are the only reform with a significant and consistent impact on liability pressure: they reduce jury awards (Hyman *et al.* 2009), settlement amounts (Avraham 2007, Friedson and Kniesner 2012), claim frequency (Avraham 2007, Waters *et al.* 2007, Paik *et al.* 2013), and insurance premiums (Thorpe 2004, Kilgore *et al.* 2006), giving rise to an overall reduction in liability pressure. Other reforms, including caps on punitive damages and modifications of the collateral-source and joint-and-several liability rule, have no significant impact on payments or claim frequency, or they increase one and decrease the other.

Several pieces of evidence suggest that changes in the tort law are not related to specific trends in medical care, such as antibiotic prescribing rates, which is crucial for the empirical analysis. First, political factors, such as the political power of the Republican party, appear to be the main drivers of tort reform, whereas private interest groups, including physician associations, do not play an important role (Deng and Zanjani 2016, Matter and Stutzer 2015). Second, most tort reforms affect all kinds of torts equally and are not limited to medical malpractice cases. In fact, many of the reforms concerning punitive damages are an indirect consequence of the public debate revolving around frivolous litigation and the infamous hot coffee lawsuit (*Liebeck v. McDonald's Restaurants*, 1992). Finally, many tort reforms have been ruled unconstitutional by state supreme courts. These court rulings are plausibly exogenous to trends in medical care and will be exploited in the empirical analysis.

[21] For two excellent surveys of the literature until the early 2000s, see Holtz-Eakin (2004) and Mello (2006).

2.3 A Model of Prescriptions under the Threat of Malpractice

This section introduces a model of the physician's decision to prescribe an antibiotic under the threat of malpractice. The physician (she) sees a patient (he) who suffers from an infection, i. The infection is either viral ($i = v$) or bacterial ($i = b$), but the physician does not observe i. Instead she observes the patient's symptoms, from which she can infer the risk that the infection is bacterial, $r = \Pr(i = b)$.

Based on the patient's symptoms, the physician has to decide whether to prescribe an antibiotic ($a = 1$) or not ($a = 0$). She chooses a to maximize her expected utility,

$$V\left(a, r \mid \text{law}\right) = U\left(a, r\right) - L\left(a, r \mid \text{law}\right) - \lambda a,$$

where $U(a, r) = ru(a \mid i = b) + (1 - r)u(a \mid i = v)$ is the patient's expected utility; $L(a, r \mid \text{law}) = rl(a \mid i = b, \text{law}) + (1 - r)l(a \mid i = v, \text{law})$ is the physician's expected medical liability; and $\lambda \geq 0$ measures how the physician internalizes the risk of increased antibiotic resistance.

The patient's expected utility is determined by his health and out-of-pocket cost, if any. An antibiotic increases the patient's health, but only in the case of a bacterial infection. On the other hand, an antibiotic can cause side effects or lead to an adverse drug reaction, and it may imply an out-of-pocket cost for the patient. Therefore, I assume that the patient prefers to receive an antibiotic if he has a bacterial infection, $u(1 \mid i = b) > u(0 \mid i = b)$, and he prefers not to receive one otherwise, $u(1 \mid i = v) < u(0 \mid i = v)$.[22] Given these two assumptions, there exists a unique and interior value of r, which is denoted by r_{pat}, such that $U(0, r_{\text{pat}}) = U(1, r_{\text{pat}})$. If the patient could prescribe an antibiotic to himself, he would do so if and only if $r \geq r_{\text{pat}}$.

The physician's expected liability is essentially the probability that a malpractice claim against her is brought forward times the monetary and nonmonetary costs that are associated with a claim, where the tort law potentially affects both the incentives for patients to sue the physician and the costs to the physician that result from a claim. In our setup, the physician can be held liable for medical malpractice for failing to prescribe an antibiotic and for provoking an adverse drug reaction. When the patient suffers from a viral infection, prescribing an antibiotic gives rise to greater expected liability than not prescribing an antibiotic, $l(1 \mid i = v, \text{law}) > l(0 \mid i = v, \text{law})$. This is because the physician cannot be held responsible for failing to prescribe an antibiotic to a patient with viral infection but she can potentially be held responsible for an adverse drug reaction. On the other hand, not giving an antibiotic to a patient with a bacterial infection can result in the patient being severely harmed and is most likely to result in a medical malpractice claim in our setup, consider-

[22]Both assumptions can be relaxed, to some extent, without affecting the results that follow in the next sections. Thus, the model can also accommodate patients with a bias towards (or against, for that matter) antibiotics.

ing that adverse drug reactions from antibiotics are relatively rare.[23] Therefore, prescribing an antibiotic minimizes expected liability when the patient suffers from a bacterial infection, $l(1 \mid i = b, \text{law}) < l(0 \mid i = b, \text{law})$. It follows that there exists a unique and interior value of r, which is denoted by r_{law}, such that $L(0, r_{\text{law}} \mid \text{law}) = L(1, r_{\text{law}} \mid \text{law})$. Furthermore, we have that $L(1, r \mid \text{law}) \geq L(0, r \mid \text{law})$ if and only if $r \leq r_{\text{law}}$.

In essence, the liability system is aligned with the patient's preferences: it is optimal to prescribe (not to prescribe) an antibiotic to a patient with a high (low) risk of bacterial infection from both a legal and patient point of view. However, the liability system must not perfectly mirror the patient's preferences.[24] For example, if $r_{\text{law}} < r_{\text{pat}}$, then the liability system exhibits a bias towards prescribing more antibiotics relative to what is optimal for the patient. In what follows, we will see that such a legal bias affects both the physician's decision to prescribe an antibiotic and the effect that tort reforms have on the physician's prescribing behavior.

2.3.1 The Physician's Prescription Decision

The physician prescribes an antibiotic if and only if $V(1, r \mid \text{law}) \geq V(0, r \mid \text{law})$. She does does not prescribe an antibiotic to a patient who is certain to have a viral infection, given that $V(1, 0 \mid \text{law}) < V(0, 0 \mid \text{law})$. If λ is sufficiently small, then $V(1, 1 \mid \text{law}) > V(0, 1 \mid \text{law})$, which implies that the physician prescribes an antibiotic to a patient who is certain to have a bacterial infection. As $V(\cdot)$ has strictly increasing differences in (a, r), the physician's optimal decision rule is a cut-off strategy: $a(r) = 1$ if $r \geq r_{\text{phy}}(\text{law})$ and $a(r) = 0$ if $r < r_{\text{phy}}(\text{law})$. The cut-off, which is denoted by $r_{\text{phy}}(\text{law})$, is interior, depends on the tort law, and is determined by the following equation:

$$\triangle U\left(r_{\text{phy}}(\text{law})\right) - \lambda = \triangle L\left(r_{\text{phy}}(\text{law}) \mid \text{law}\right), \tag{2.1}$$

where $\triangle U(r) \equiv U(1, r) - U(0, r)$ and $\triangle L(r \mid \text{law}) \equiv L(1, r \mid \text{law}) - L(0, r \mid \text{law})$.

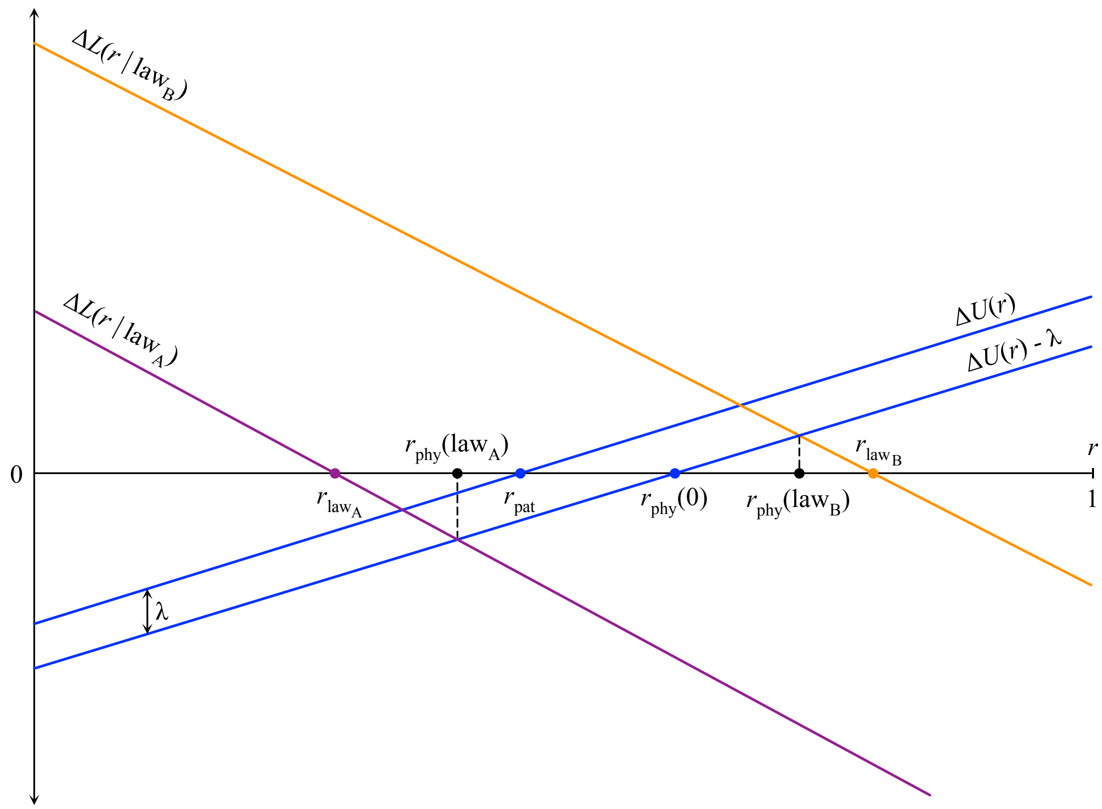
For the marginal patient, the incremental expected utility from receiving an antibiotic minus the cost the physician attributes to the risk of increased antibiotic resistance is equal to the increment in expected liability due to the antibiotic prescription. The physician's optimal choice is depicted in Figure 2.1, where $r_{\text{phy}}(0)$ is the cut-off the physician would choose in the absence of a liability system. The physician's cut-off as a function of the law is characterized as follows.

Proposition 3. $r_{\text{phy}}\,(\text{law})$ *is unique and satisfies* $\min\{r_{\text{phy}}(0), r_{\text{law}}\} \leq r_{\text{phy}}\,(\text{law}) \leq \max\{r_{\text{phy}}(0), r_{\text{law}}\}$, where the inequalities are strict if $r_{\text{phy}}(0) \neq r_{\text{law}}$.

[23] Less than two percent of the patients in a sample of Medicare enrollees taking antibiotics in the ambulatory care setting experienced an adverse drug reaction (Gurwitz *et al.* 2003).

[24] In this regard, the model departs from Shurtz (2014) and other studies in the literature that assume a perfect liability system.

Figure 2.1: The physician's prescription decision



Notes: Figure depicts the physician's prescription decision for two different legal regimes. If the patient could decide for himself, he would choose to receive an antibiotic whenever $r \geq r_{\text{pat}}$. If there was no liability system, the physician would prescribe an antibiotic whenever $r \geq r_{\text{phy}}(0)$. Under the purple legal regime, law_{A}, the physician prescribes an antibiotic whenever $r \geq r_{\text{phy}}(\text{law}_{\text{A}})$. Under the orange legal regime, law_{B}, the physician prescribes an antibiotic whenever $r \geq r_{\text{phy}}(\text{law}_{\text{B}})$.

Proof: Define $\triangle V(r \mid \text{law}) \equiv V(1, r \mid \text{law}) - V(0, r \mid \text{law})$ and note that $\triangle V(\cdot \mid \text{law})$ is strictly increasing and $r_{\text{phy}}(\text{law})$ solves $\triangle V(r \mid \text{law}) = 0$. This implies that $r_{\text{phy}}(\text{law})$ is unique. Suppose that $r_{\text{phy}}(0) < r_{\text{law}}$. Note that $\triangle V(r_{\text{phy}}(0) \mid \text{law}) = -\triangle L(r_{\text{phy}}(0) \mid \text{law}) < 0$ since $\triangle L(\cdot \mid \text{law})$ is strictly decreasing and $r_{\text{phy}}(0) < r_{\text{law}}$. Since $\triangle V(\cdot \mid \text{law})$ is strictly increasing, it must be that $r_{\text{phy}}(\text{law}) > r_{\text{phy}}(0)$. Moreover, we have that $\triangle V(r_{\text{law}} \mid \text{law}) = \triangle U(r_{\text{law}}) - \lambda > 0$ since $\triangle U(\cdot)$ is strictly increasing and $r_{\text{law}} > r_{\text{phy}}(0)$. It follows that $r_{\text{phy}}(0) < r_{\text{phy}}(\text{law}) < r_{\text{law}}$. The other two cases follow analogously. *Q.E.D.*

The physician's cut-off will generally differ from the patient's preferred cut-off because the physician balances her concern for the patient's utility against the legal implications of the prescription decision and the risk of increased antibiotic resistance. If the tort law introduces a bias against prescribing antibiotics relative to what is optimal for the patient, such as law_{B} in Figure 2.1, then the physician will prescribe fewer antibiotics than the patient desires. On the other hand, the physician may also prescribe more antibiotics than what is optimal for the patient. This happens when the tort law exhibits a sufficiently large bias towards prescribing antibiotics, such as law_{A} in Figure 2.1.

2.3.2 Tort Reforms and Antibiotic Prescriptions

Applying the implicit function theorem to equation (2.1) yields the effect of a marginal change in the tort law on the cut-off that the physician applies to prescribe an antibiotic:

$$\frac{dr_{\text{phy}}(\text{law})}{d\text{law}} = \frac{\triangle L_{\text{law}}(r_{\text{phy}}(\text{law}) \mid \text{law})}{\triangle U_r(r_{\text{phy}}(\text{law})) - \triangle L_r(r_{\text{phy}}(\text{law}) \mid \text{law})}. \tag{2.2}$$

The denominator is positive, so that the sign of the tort reform's effect on $r_{\text{phy}}(\text{law})$ is the same as the sign of the numerator in equation (2.2). In order to proceed, it is necessary to take a stance on the effect of tort reforms on the liability pressure that physicians experience. I make the following assumption in this regard.

Assumption 2. *Tort reforms have a proportional impact on the liability pressure that physicians experience:* $L_{\text{law}}(a, r \mid \text{law}) = \mu L(a, r \mid \text{law})$ *for all* a, r, *and* law.

In other words, tort reforms have a greater effect on the liability pressure resulting from high-risk patients and medication treatments than on the pressure resulting from low-risk patients and medication treatments. As such, tort reforms that increase the liability pressure on physicians ($\mu > 0$) disproportionately increase the liability pressure that physicians experience while treating high-risk patients and performing high-risk medication treatments. Tort reforms that satisfy Assumption 2 have the appealing feature that they do not change the cut-off r_{law}, which determines when, in expectation, it is preferred from a legal perspective to prescribe an antibiotic and when not. In practice, tort reforms are not enacted to increase or decrease the use of a specific medical procedure. Any theory that would predict a change in the cut-off r_{law} after a reform would therefore be hard to rationalize. Besides that, Assumption 2 is also compatible with several functional forms for the liability function that are commonly adopted in the medical malpractice literature.[25]

We are now in a position to characterize the effect of tort reforms on antibiotic prescriptions.

Proposition 4. *Suppose that Assumption 2 holds. A liability-reducing tort reform, such as a cap on noneconomic damages, causes physicians to prescribe fewer (more) antibiotics if and only if* $r_{\text{law}} < (>)\ r_{\text{phy}}(0)$.

Proof: Assumption 2 implies that $\triangle L_{\text{law}}(r \mid \text{law}) = \mu \triangle L(r \mid \text{law})$ for all r and law. Substituting into equation (2.2), we obtain sign$\{dr_{\text{phy}}(\text{law})/d\text{law}\} = $ sign$\{\mu \triangle L(r_{\text{phy}}(\text{law}) \mid \text{law})\}$, which boils down to sign$\{dr_{\text{phy}}(\text{law})/d\text{law}\} = $ sign$\{-\triangle L(r_{\text{phy}}(\text{law}) \mid \text{law})\}$ in the case of a liability-reducing tort reform. Proposition 3 shows that $r_{\text{phy}}(\text{law}) > (<)\ r_{\text{law}}$ if and only if $r_{\text{law}} < (>)\ r_{\text{phy}}(0)$. Recalling that $\triangle L(\cdot \mid \text{law})$ is strictly decreasing and $\triangle L(r_{\text{law}} \mid \text{law}) = 0$, it follows that $dr_{\text{phy}}(\text{law})/d\text{law} > (<)\ 0$ in the case of a liability-reducing tort reform if and only if $r_{\text{law}} < (>)\ r_{\text{phy}}(0)$. *Q.E.D.*

Figure 2.2 illustrates Proposition 4. We see that a tort reform that puts less liability pressure on physicians can increase or decrease the number of antibiotic prescriptions. The effect of the reform depends on whether the liability system introduces a bias towards or against prescribing antibiotics relative to what the physician would choose in the absence of a liability system. If the liability system introduces a bias towards prescribing more antibiotics, such as law_{A}, then a reduction in liability pressure will lead physicians to prescribe fewer antibiotics. Conversely, if the liability system introduces a bias against prescribing antibiotics, such as law_{B}, then a reduction in liability pressure implies more antibiotic prescriptions.

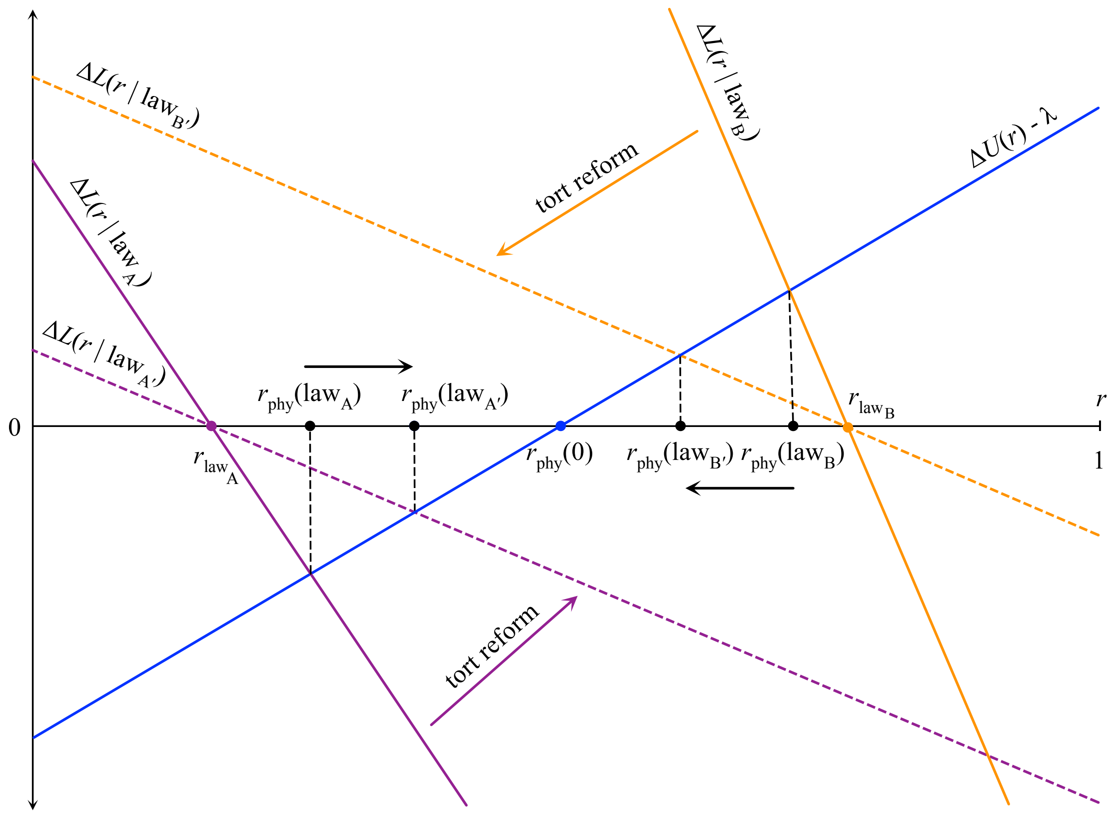
2.3.3 The Social Optimum and Defensive Medicine

The social planner trades off the patient's benefit against the social cost of increased antibiotic resistance. He chooses a to maximize $W(a, r) = U(a, r) - \lambda^* a$, where the social cost of increased antibiotic resistance, λ^*, is potentially different from the cost that the physician takes into account, λ. Not surprisingly, the social optimum is also characterized by a cut-off, which is denoted by r^*, so that it is socially optimal to prescribe an antibiotic if and only if $r \geq r^*$. Given that λ^* is sufficiently small, this cut-off is interior and uniquely determined by

$$\triangle U\left(r^*\right) - \lambda^* = 0. \tag{2.3}$$

[25] One example that satisfies Assumption 2 is the liability function proposed by Shurtz (2014), according to which the tort law affects only the cost to the physician that results from a malpractice claim and not the patient's propensity to sue the physician.

Figure 2.2: The effect of a liability-reducing tort reform on prescriptions



Notes: Figure depicts the effect of a liability-reducing tort reform on antibiotic prescriptions for two different legal regimes, law$_A$ and law$_B$, where the former is more in favor of antibiotics than the latter. Tort reforms that satisfy Assumption 2 correspond to a rotation of the function $\triangle L(\cdot \mid \text{law})$ around the cut-off r_{law}. Under the purple legal regime, law$_A$, a reduction in liability pressure leads to a decrease in antibiotic prescriptions given that $r_{\text{law}_A} < r_{\text{phy}}(0)$. As $r_{\text{law}_B} > r_{\text{phy}}(0)$, a reduction in liability pressure causes an increase in antibiotic prescriptions under the orange legal regime, law$_B$.

Defensive medicine is defined with respect to the socially optimal level of care: medical care for which the expected social cost exceeds the expected social benefit is considered defensive if it is delivered to avoid potential litigation. In our setup, the expected social cost of an antibiotic exceeds its expected social benefit whenever $r < r^*$. Now if $r_{\text{phy}}(\text{law}) < r^*$, then the physician will prescribe some socially wasteful antibiotics. However, only in the case in which $r_{\text{phy}}(\text{law}) < r_{\text{phy}}(0)$ does the physician prescribe antibiotics to protect herself against the risk of malpractice, for if $r_{\text{phy}}(\text{law}) > r_{\text{phy}}(0)$ then the tort law actually induces the physician to prescribe fewer antibiotics. Therefore, we can say that the physician prescribes antibiotics defensively if and only if $r_{\text{phy}}(\text{law}) < r_{\text{phy}}(0)$ and $r_{\text{phy}}(\text{law}) < r^*$.

How do we know whether these two inequalities are satisfied in practice? From Propositions 3 and 4, we can deduce that the first inequality holds if a liability-reducing tort reform leads physicians to prescribe fewer antibiotics. But without further assumptions, the model is silent about the second inequality. In order to arrive at a test of defensive medicine, I introduce the following assumption.

Assumption 3. *The physician internalizes weakly less of the risk of increased antibiotic resistance than the social planner:* $\lambda \leq \lambda^*$.

In surveys, physicians report that they believe that their prescribing behavior does not significantly affect antibiotic resistance (Kumar *et al.* 2003), that antibiotic resistance carries the least weight in their prescription decision (Metlay *et al.* 2002), and that antibiotic resistance is a community issue and less important than the well being of the individual patient (Butler *et al.* 1998). In light of these self-reports, it seems reasonable to assume that physicians do not fully internalize the cost of increased antibiotic resistance.

Assumption 3 implies that physicians tend to prescribe more antibiotics than socially optimal if there is no liability system in place: $r_{\text{phy}}(0) \leq r^*$.[26] Given this, we know that $r_{\text{phy}}(\text{law}) < r_{\text{phy}}(0)$ is a necessary and sufficient conditions for the two inequalities that determine whether antibiotics are prescribed defensively to be satisfied. The following corollary, which represents the central result of the theoretical analysis, summarizes how we can use tort reforms to test for defensive medicine.

Corollary 2. *Suppose that Assumptions 2 and 3 hold. Antibiotics are prescribed defensively if and only if a liability-reducing tort reform, such as a cap on noneconomic damages, causes a decrease in antibiotic prescriptions.*

[26] Apart from not internalizing the risk of increased antibiotic resistance, there may be other reasons why physicians prescribe more antibiotics than socially optimal. Physicians tend not to internalize the part of the drug cost that health insurance companies have to bear (Lundin 2000, Iizuka 2007). Physicians may also hope to attract new patients or retain current ones by prescribing antibiotics (Bennett *et al.* 2015). Finally, physicians may also prescribe antibiotics because they are receptive to marketing efforts by pharmaceutical companies. On the other hand, there seems to be only one factor that explains why physicians would prescribe fewer antibiotics than socially optimal, which is that they do not consider the positive effect that curing one patient's bacterial infection has on the patient's social network. It seems unlikely that this factor alone could tilt the balance towards physicians prescribing fewer antibiotics than socially optimal in the absence of a liability system.

In the empirical analysis, I will exploit noneconomic damages cap reforms to obtain causal estimates of the effect of a reduction in liability pressure on antibiotic prescriptions and use these estimates to test for defensive medicine along the lines of Corollary 2. I will complement this approach with a traditional test of defensive medicine à la Kessler and McClellan (1996), in which I contrast changes in antibiotic prescriptions after noneconomic damages cap reforms with corresponding changes in health outcomes that can potentially be improved by antibiotic use.

2.4 Data and Summary Statistics

2.4.1 National Ambulatory Medical Care Survey

The National Ambulatory Medical Care Survey is a nationally representative survey of visits to non-federal employed office-based physicians in the U.S., excluding anesthesiologists, pathologists, and radiologists. The National Center for Health Statistics (NCHS), which conducts the survey, employs a three-stage sampling procedure. Each of the about 1,200 physicians who participate annually in the survey is randomly assigned to a one-week reporting period, during which data is collected for a systematic random sample of about 25 patients. Physicians and patients may be sampled in multiple years, but it is not possible to identify longitudinal linkages.

For each visit, the data contains the patient's symptoms, the physician's diagnosis according to the ICD-9-CM, and treatments and medications ordered or provided. Antibiotic prescriptions can be identified using the NCHS-assigned five-digit medication codes in conjunction with the NCHS Ambulatory Care Drug Database System (see Appendix 2.A for more details). Geographic information in the public-use NAMCS data files is limited and restricted to identifiers indicating census region and MSA status. I obtained access to restricted-use NAMCS data at the NCHS Research Data Center, through which it was possible to identify the county and state in which physician practices are located. This information was used to assign the corresponding state tort laws to physicians.

The left panel of Table 2.1 contains descriptive statistics for the key variables from the NAMCS. The data corresponds to the survey years from 1993 to 2011 and includes a total of 546,990 patient visits. On average, physicians prescribe about two drugs per ambulatory care visit. Antibiotics, which are coded as a dummy variable, are prescribed in about one in eight visits. When physicians prescribe antibiotics, they mostly prescribe broad-spectrum antibiotics, which act against a wider range of bacteria but also imply a higher risk of increased antibiotic resistance than narrow-spectrum antibiotics.

Table 2.1: Descriptive statistics of key variables

	NAMCS			NIS		
	Mean	SE	N	Mean	SE	N
Prescription outcomes						
Any kind of antibiotic	0.1271	(0.0015)	543,125			
Broad-spectrum antibiotic	0.0902	(0.0012)	543,018			
Narrow-spectrum antibiotic	0.0367	(0.0006)	543,018			
Number of drugs	1.8583	(0.0224)	543,125			
Health outcomes						
Peritonsillar abscess				0.0004	(0.0000)	141,417,785
Rheumatic fever				0.0000	(0.0000)	141,417,785
Mastoiditis				0.0001	(0.0000)	141,417,785
Septicemia				0.0134	(0.0002)	141,417,785
Pneumonia				0.0315	(0.0002)	141,417,785
Meningitis				0.0003	(0.0000)	141,417,785
Patient						
Female	0.5908	(0.0016)	546,990	0.5869	(0.0009)	141,278,661
Age	44.1265	(0.1849)	546,990	47.2901	(0.1785)	141,392,820
White	0.7546	(0.0095)	513,882	0.6887	(0.0056)	110,044,140
Black	0.0947	(0.0037)	513,882	0.1421	(0.0038)	110,044,140
Latino	0.1085	(0.0081)	513,882	0.1137	(0.0040)	110,044,140
Insurance						
Private	0.5612	(0.0056)	529,019	0.3621	(0.0032)	141,052,576
Medicare	0.2219	(0.0033)	529,019	0.3664	(0.0026)	141,052,576
Medicaid	0.1119	(0.0037)	529,019	0.1855	(0.0027)	141,052,576

Notes: Standard errors accounting for complex survey design in parentheses.

2.4.2 Nationwide Inpatient Sample

The Nationwide Inpatient Sample is part of the Healthcare Cost and Utilization Project (HCUP), which is sponsored by the Agency for Healthcare Research and Quality. Covering about seven million hospital stays each year, the NIS constitutes the largest publicly available all-payer inpatient healthcare database in the U.S. The data is collected annually from about 1,000 hospitals, which are sampled to approximate a 20-percent stratified sample of U.S. community hospitals, where each hospital reports on all discharges that occur throughout the year. The NIS records include ICD-9-CM codes for the diagnoses and procedures that patients receive, as well as patient and hospital characteristics. Until 2011, the NIS data also includes identifiers for the county and state in which hospitals are located, which were used to assign hospitals the corresponding state tort laws. Not all states participate in the HCUP, but the number of states that do has grown over time (from 8 in 1988 to 17 in 1993 to 46 in 2011).

The right panel of Table 2.1 contains descriptive statistics for the key variables from the NIS. The data corresponds to the survey years from 1993 to 2011 and includes a total of 142,002,152 inpatient stays. The six health outcomes that are listed in the table represent complications that can potentially be prevented by antibiotic use in primary care. Each complication is captured by a dummy variable that equals one if the primary diagnosis corresponds to the complication.[27] Some of these complications, such as rheumatic fever, represent only a tiny fraction of all inpatient stays. Septicemia and pneumonia, however, together account for almost five percent of all inpatient stays during the sample period, corresponding to almost 7 million observations. Patient demographics are similar between the NAMCS and NIS data, but the fraction of privately insured patients is lower in the NIS data.

2.4.3 State Tort Laws

I collected information about the state tort laws from various sources and merged it onto the NAMCS and NIS data. I built on Ronen Avraham's Database of State Tort Law Reforms (Avraham 2014) and the state law data provided in an appendix to Currie and MacLeod (2008) and supplemented these two sources with information from the American Tort Reform Association and the state codes. The final product is a dataset covering the four reforms discussed earlier – caps on noneconomic damages, caps on punitive damages, modifications of the collateral-source rule, and modifications of the joint-and-several liability rule – and the years from 1992 to 2012 on a monthly basis, where the years 1992 and 2012 are covered to allow for the inclusion of reform lags and leads of up to one year. Following Frakes (2012), I say that noneconomic damages are capped if a state caps the total amount of damages that

[27] The corresponding ICD-9-CM codes are 475 for peritonsillar abscess, 390-392 for rheumatic fever, 383 for mastoiditis, 038 for septicemia, 481-486 for pneumonia (bacterial or unspecified), and 320 and 322 for meningitis (bacterial or unspecified).

Table 2.2: Noneconomic damages cap reforms, 1993-2011

Cap enacted			Cap repealed		
IL	03/09/1995	$500,000$^+$	IL	12/18/1997	$500,000$^+$
ND	08/01/1995	$500,000*	OH	02/25/1998	$1,000,000
MT	10/01/1995	$250,000*	OR	07/15/1999	$500,000
OH	01/27/1997	$1,000,000	WI	07/14/2005	$350,000*$^+$
NV	10/01/2002	$350,000*	IL	02/04/2010	$500,000*
MS	01/01/2003	$500,000*	GA	03/22/2010	$350,000*
OK	07/01/2003	$300,000*			
TX	09/01/2003	$250,000*			
GA	02/16/2005	$350,000*			
SC	07/01/2005	$350,000*			
IL	08/24/2005	$500,000*			
WI	04/06/2006	$750,000*			
NC	10/01/2011	$500,000*			
TN	10/01/2011	$1,000,000			

Notes: * indicates that the cap applies only to medical malpractice rather than to all torts. $^+$ indicates that the cap is adjusted for inflation on a regular basis.

can be awarded.[28]

Recall that the literature on the effect of tort reforms on the medical malpractice environment says that caps on noneconomic damages are the only policy that have a clear-cut impact on liability pressure. For this reason, I focus on noneconomic damages caps to identify the effect of liability pressure on prescription and health outcomes. Table 2.2 lists the 20 noneconomic damage cap reforms that have taken place over the sample period. In total, 14 different states enacted tort reforms between 1993 and 2011.

2.5 Empirical Strategy

The empirical strategy is based on the assumption that states that adopt noneconomic damages caps would, if they had not adopted a cap, experience the same trends in prescription and health outcomes as states that do not adopt noneconomic damages caps. This assumption leads to the following difference-in-differences specification, which can be consistently estimated by ordinary least squares (OLS),

$$Y_{ist} = \alpha + \beta \text{CAP}_{st} + \gamma X_{ist} + \delta Z_{st} + \theta_t + \phi_s + \varepsilon_{ist}. \tag{2.4}$$

[28]This rule applies to four states (Indiana, Nebraska, South Dakota, and Virginia), all of which enact the total damages cap before the beginning of the sample period and do not experience a change in the noneconomic damages cap indicator during the sample period.

The subscripts i, s, and t stand for, respectively, a visit, a state, and a year-month combination. Y_{ist} represents a prescription or health outcome. CAP$_{st}$ indicates whether state s imposes a cap on noneconomic damages in period t. X_{ist} is a vector of controls and includes dummies for patient age (<5, 5-17, 18-44, 45-64, 65-79, 80+), patient gender, patient race and ethnicity (white, black, latino, other), patient health insurance (private, Medicare, Medicaid, other), physician degree (MD, DO), physician specialty (14 categories), physician age (<35, 35-54, 55+), physician gender, and practice/hospital location (MSA, non-MSA).[29] Z_{st} controls for the presence of caps on punitive damages, modifications of the collateral-source rule, and modifications of the joint-and-several liability rule. θ_t and ϕ_s are year-month and state dummies, respectively, and ε_{ist} is the error term. Throughout the analysis, I use the sampling weights that are provided by the NAMCS. As is customary in the estimation of difference-in-differences models with policies that vary at the state level, I report standard errors that are clustered at the state level (Bertrand *et al.* 2004).

I focus on the following prescription outcomes: the prescription of any kind of antibiotic, the prescription of narrow- or broad-spectrum antibiotics, the total number of medications prescribed (which is topcoded at 5 in 1993/1994, at 6 from 1995 to 2002, and at 8 from 2003 onwards), and the prescription of antibiotic substitutes. Following Little *et al.* (2002) and other studies in the medical literature, I consider the following six health conditions that can potentially be avoided through antibiotic use in primary care: peritonsillar abscess (quinsy), rheumatic fever, mastoiditis, septicemia, pneumonia, and meningitis. If noneconomic damages caps influence the physicians' prescribing behavior but do not affect any of the related health outcomes, this would be evidence of defensive medicine.

To study which doctors and patients are particularly affected by noneconomic damages caps, I estimate models that include interaction terms between the cap indicator and variables such as the patient's type of health insurance and the physician's association to an HMO, which have previously been identified as sources of heterogeneity in the malpractice literature. Finally, I conduct a variety of tests to assess the validity of the results, including tests that support the notion that noneconomic damages cap reforms are exogenous and not driven by preexisting trends in the outcome variables.

2.6 Results

2.6.1 Prescription Outcomes

Table 2.3 shows how noneconomic damages caps affect antibiotic prescriptions and the total number of drugs prescribed. The introduction of a noneconomic damages cap implies that doctors are 0.8 percentage points less likely to prescribe an antibiotic, which translates into

[29]The controls for physician characteristics are included only in prescription outcome regressions as this kind of information is not available in the NIS data.

Table 2.3: Impact of noneconomic damages caps on antibiotic and all prescriptions

	Any antibiotic	Broad-spectrum antibiotic	Narrow-spectrum antibiotic	Number of drugs
CAP	-6.30***	-4.77	-10.63***	-0.02
	(2.05)	(2.99)	(3.82)	(3.35)
R^2	0.07	0.06	0.02	0.23
N	479,009	478,914	478,914	479,009

Notes: Table reports results from OLS estimation of equation (2.4). The coefficients on the cap on noneconomic damages and the corresponding standard errors, which are shown in parentheses, are divided by the mean of the dependent variable and multiplied by 100. Standard errors are adjusted for clustering at the state level. * p<0.1, ** p<0.05, *** p<0.01.

a reduction of 6.3 percent over baseline. This effect is statistically and economically significant. Using the NAMCS survey weights to extrapolate the effect to the U.S. population as a whole, I estimate that, in the year 2011 alone, there would have been about 3.2 million fewer ambulatory care visits that culminate in the prescription of antibiotics if all states had adopted a cap on noneconomic damages (29 states had an active cap at the end of 2011). To put this number into perspective, in total, doctors prescribe antibiotics in about 120 million ambulatory care visits per year. Hence, through the introduction of noneconomic damages caps, one could achieve a reduction of ambulatory care visits with antibiotic prescriptions of almost 3 percent.

Comparing the second and third column of Table 2.3, we see that narrow-spectrum antibiotics are statistically significantly affected by the introduction of noneconomic damages caps, whereas broad-spectrum antibiotics are not affected. It appears that physicians do not value the additional legal protection that broad-spectrum antibiotics can offer in certain cases, or that other factors – such as the higher cost of broad-spectrum antibiotics, the higher risk of side effects, and the bigger impact on antibiotic resistance that broad-spectrum antibiotics have compared to narrow-spectrum antibiotics – outweigh the benefits of broad-spectrum antibiotics for the marginal patient.

From Column 4 of Table 2.3, we can infer that physicians do not adjust the number of drugs they prescribe in response to noneconomic damages cap reforms. This suggests that doctors substitute other drugs for antibiotics when they face less liability pressure. To determine which medications doctors substitute for antibiotics, I turn to the drugs that are most frequently prescribed together with antibiotics or for conditions for which antibiotics are commonly prescribed. These are antiinflammatory drugs, such as Tylenol, Advil, and Aspirin, antihistamines, antitussives, decongestants, expectorants, and upper respiratory combinations (URC). Table 2.4 shows that, out of these drugs, only antitussives (a form of cough medica-

Table 2.4: Impact of noneconomic damages caps on antibiotic substitutes

	Tylenol	Advil	Aspirin	Antihistamines	Antitussives	Decongestants	Expectorants	URC
CAP	-6.03	0.79	-9.60	9.74	47.33*	-19.55	24.11	-25.39
	(15.08)	(13.51)	(18.19)	(9.26)	(25.63)	(17.77)	(15.50)	(18.56)
R^2	0.02	0.02	0.05	0.02	0.01	0.01	0.01	0.01
N					479,009			

Notes: Table reports results from OLS estimation of equation (2.4). The coefficients on the cap on noneconomic damages and the corresponding standard errors, which are shown in parentheses, are divided by the mean of the dependent variable and multiplied by 100. Standard errors are adjusted for clustering at the state level. * p<0.1, ** p<0.05, *** p<0.01.

tion that is marketed, inter alia, under the brand name Codeine) are statistically significantly affected by the introduction of noneconomic damages caps. As doctors prescribe more antitussives after the introduction of noneconomic damages caps, it appears that antitussives act as a substitute for antibiotics. From a medical standpoint, this is actually a desirable substitution, given that antitussives represent a more effective treatment option than antibiotics for many cases of upper respiratory tract infections (Zanasi *et al.* 2016).

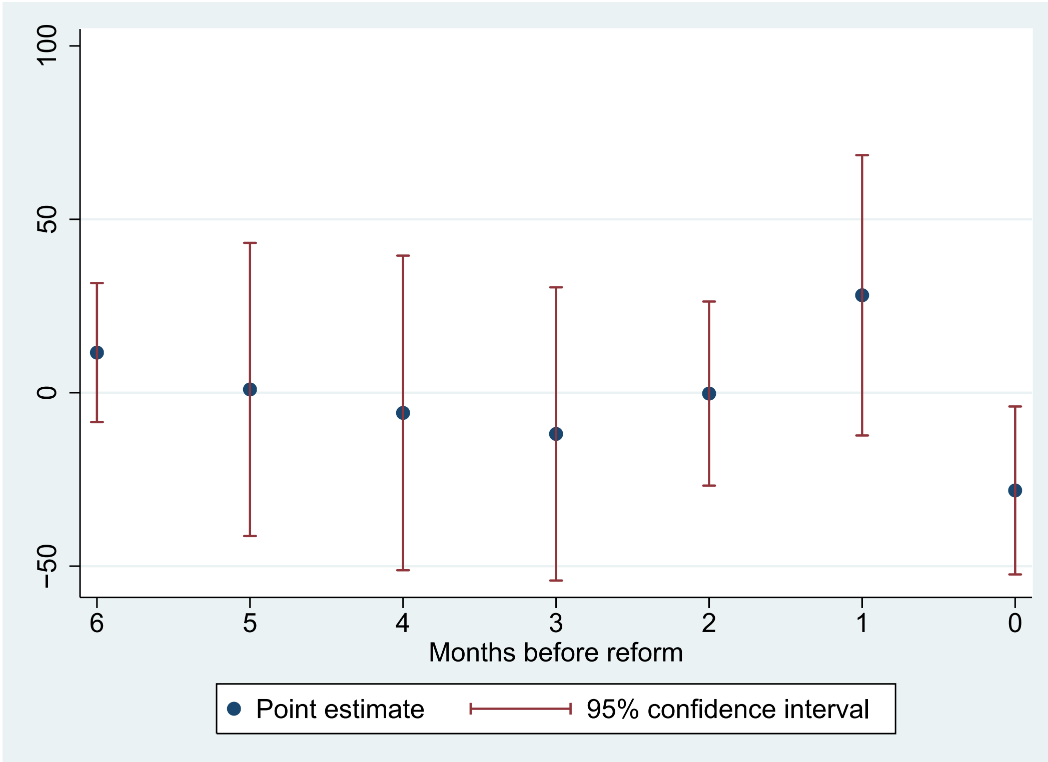
Table 2.5 shows that noneconomic damages caps do not affect all patients equally. Patients aged 80 and above, for example, are not less likely to be prescribed an antibiotic after the introduction of a noneconomic damages cap, which can be explained by the fact that older patients pose less of a malpractice risk to physicians because of lower future earnings losses and fewer years of pain and suffering. This result is also reflected in the estimates shown in the second panel of Table 2.5, which reveal that physicians do not adjust antibiotic prescriptions in response to noneconomic damages caps for Medicare patients, who are predominantly aged 65 years and above. The second panel moreover illustrates that physicians react more strongly to caps when the patient's health insurance belongs to the category "other", which includes self-pay, worker's compensation, and no charge. One explanation for this finding is that many physicians (falsely) believe that low-income patients, who often have no health insurance coverage, are more likely to sue for medical malpractice than other patients (McClellan *et al.* 2012). The third panel of Table 2.5 shows that physicians who work in HMO-owned practices do not react differently to noneconomic damages caps than their peers who work in practices that are not owned by HMOs, at least not in statistical terms. However, this finding should not be viewed as conclusive evidence given that there are only few observations of physicians practicing in HMOs and given that the variable that indicates whether a practice is owned by an HMO is not available in all survey years. Finally, there is no statistical evidence suggesting that older physicians react differently to caps on noneconomic damages

Table 2.5: Impact of noneconomic damages caps on subgroups

Patient age		Health insurance		HMO	
CAP × 0-4	-11.41	CAP × private	-6.38***	CAP	-7.08**
	(9.92)		(2.28)		(2.68)
CAP × 5-17	-2.28	CAP × Medicare	-0.47	CAP × HMO	-9.52
	(5.98)		(3.62)		(8.58)
CAP × 18-44	-10.78***	CAP × Medicaid	-7.87		
	(2.44)		(5.67)		
CAP × 45-64	-7.16**	CAP × other	-16.21***		
	(3.46)		(2.52)		
CAP × 65-79	-3.38				
	(3.70)				
CAP × 80+	7.56				
	(4.88)				
R^2	0.07		0.07		0.06
N	479,009		479,009		356,947

Notes: Table reports results from OLS estimation of equation (2.4) augmented for interaction terms. The dependent variable is a dummy indicating any antibiotic prescription. Coefficients and standard errors (in parentheses) are divided by the mean of the dependent variable and multiplied by 100. Standard errors are adjusted for clustering at the state level. * p<0.1, ** p<0.05, *** p<0.01.

Figure 2.3: Preprogram regressions



Notes: Figure reports results from OLS estimation of equation (2.4), where the dependent variable is a dummy indicating any antibiotic prescription and the regression model includes dummies that equal one in from one to six months before a noneconomic damages cap is enacted. Standard errors corresponding to the confidence intervals are adjusted for clustering at the state level. Point estimates and confidence intervals are expressed as a percentage of the mean antibiotic prescription rate.

than younger physicians, or that primary care physicians react differently than specialists, or that general practitioners and pediatricians behave differently from the rest of their peers.

2.6.2 Threads to Validity

The main identifying assumption behind every difference-in-differences setup is that the treatment and control group would experience parallel trends if both were left untreated. Legislative endogeneity – the possibility that preexisting trends in the medical care sector cause tort reforms – poses a threat to the parallel trends assumption. Figure 2.3 and Table 2.6 present four pieces of evidence suggesting that noneconomic damages cap reforms are causing a change in antibiotic prescriptions and not vice versa. Figure 2.3 contains the results of so-called preprogram regressions (Heckman and Hotz 1989), which reveal that states that adopt noneconomic damages caps have statistically similar antibiotic prescription rates in the six months leading up to the reforms as states that do not adopt caps. Column 1 of Table 2.6

Table 2.6: Further tests for legislative endogeneity

	Only caps turning off	Only caps nonspecific to medical malpractice	State-specific time trends
CAP	5.67***	-3.15	-6.61
	(1.73)	(5.82)	(5.12)
R^2	0.07	0.07	0.07
N	479,009	479,009	479,009

Notes: Table reports results from OLS estimation of equation (2.4), where the dependent variable is a dummy indicating any antibiotic prescription. Column 1 reports the coefficient on a dummy that equals one as long as a noneconomic damages cap has been turned off. Column 2 reports the coefficient on an indicator for caps on noneconomic damages that are not specific to medical malpractice. Column 3 reports the coefficient on the noneconomic damages cap indicator from a model that includes state-specific linear and quadratic time trends. Standard errors adjusted for clustering at the state level in parentheses. All coefficients and standard errors are divided by the mean of the dependent variable and multiplied by 100. * p<0.1, ** p<0.05, *** p<0.01.

illustrates that when noneconomic damages caps are turned off, which arguably resembles a truly exogenous change in liability pressure given that caps are turned off almost exclusively because they are ruled unconstitutional, we also find a statistically significant effect on antibiotic prescriptions (positive in this case, because liability pressure increases). Column 2 of 2.6 shows that noneconomic damages caps that are not specific to medical malpractice have a similar impact on antibiotic prescriptions as caps that are specific to malpractice.[30] Finally, Column 3 of 2.6 shows that the inclusion of state-specific time trends, while leading to a sharp increase in the standard errors of the estimates, does not quantitatively affect how noneconomic damages caps influence antibiotic prescriptions.

Apart from nonparallel trends, one may also be worried about fitting a linear model to binary dependent variables. Fortunately, Table 2.7 shows that a Probit model yields similar results as the linear probability model. Table 2.7 moreover shows that the use of sampling weights is not driving the results and that excluding observations for which one or more of the covariates are imputed does not affect the results either.

A final issue concerns the choice of covariates in equation (2.4). To mitigate potential concerns about bad controls (see, for example, Angrist and Pischke 2008), I have estimated

[30] Note that only five out of 20 noneconomic damages caps reforms are not specific to medical malpractice, which contributes to the coefficient on the cap being no longer statistically significant.

Table 2.7: Sensitivity Analysis

	Probit	no weights	excluding imputed	no controls full sample	no controls restricted sample	only visit-level controls	only state-level controls
CAP	-5.82***	-5.30*	-6.30**	-1.26	-7.24*	-5.90**	-3.38
	(2.05)	(2.65)	(2.44)	(2.52)	(3.96)	(2.36)	(2.52)
R^2	0.10	0.07	0.07	0.01	0.03	0.07	0.01
N	479,009	479,009	378,160	543,125	127,202	479,009	543,125

Notes: Table reports results from estimation of equation (2.4). Column 1 reports the average marginal effect of the cap indicator from a Probit model. Column 2 reports the results from an OLS model that does not use survey weights. Column 3 reports the results from an OLS model that excludes observations with imputed values. Columns 4 and 5 report the results from an OLS model excluding the controls X and Z. Column 4 reports the results for the whole sample, and Column 5 reports the result for the sample of patients who visit the physician with symptoms of respiratory conditions. Columns 6 and 7, respectively, report results from OLS models that exclude the controls X and Z. Standard errors adjusted for clustering at the state level in parentheses. All coefficients and standard errors are divided by the mean of the dependent variable and multiplied by 100. * p<0.1, ** p<0.05, *** p<0.01.

the baseline model with different sets of controls (see Table 2.7) and included the covariates one by one as dependent variables in what I call bad control tests (see Table 2.12 in Appendix 2.B). Not controlling for visit-level controls such as the patient's age and race leads to a large drop in the R-squared of the regression model, resulting in insignificant coefficients on the cap on noneconomic damages. But, restricting the sample to patients who visit the physician with symptoms related to respiratory conditions, who arguably are the main driver behind the effect of noneconomic damages caps on antibiotic prescriptions, restores significance of the coefficient on the cap on noneconomic damages. The bad control tests in Table 2.12 reveal no change in patient and physician characteristics after noneconomic damages cap reforms, with one exception: Ambulatory care physicians seem to take up more privately insured patients and fewer Medicare patients, who are older on average. If these privately insured patients are the riskier cases that doctors were unwilling to take up without caps on damages, then we might expect this change in the patient population to have a positive impact on the antibiotic prescription rate. This would mean that my results are conservative estimates of the true effect of noneconomic damages caps on antibiotic prescriptions.

2.6.3 Health Outcomes

All in all, the results presented so far suggest that physicians prescribe more antibiotics in response to liability pressure. What we do not know is whether these antibiotics are socially wasteful or not. If the assumptions of the theoretical model hold, then we should believe that

Table 2.8: Impact of noneconomic damages caps on health outcomes (I)

	Peritonsillar abscess	Rheumatic fever	Mastoiditis	Septicemia	Pneumonia	Meningitis
CAP	7.57	-8.33	26.02**	3.84	3.37	-11.46***
	(6.98)	(9.79)	(9.94)	(5.16)	(3.45)	(3.58)
R^2	0.00	0.00	0.00	0.01	0.02	0.00
N			98,275,213			

Notes: Table reports results from OLS estimation of equation (2.4). The coefficients on the cap on noneconomic damages and the corresponding standard errors, which are shown in parentheses, are divided by the mean of the dependent variable and multiplied by 100. Standard errors are adjusted for clustering at the state level. * p<0.1, ** p<0.05, *** p<0.01.

they are: the model predicts that antibiotics are prescribed defensively if a liability-reducing tort reform, such as a cap on noneconomic damages, causes a decrease in antibiotic prescriptions. To provide further evidence on this matter, we will now turn to a test of defensive medicine à la Kessler and McClellan (1996), for which we contrast the changes in antibiotic prescriptions with changes in health conditions that can potentially be prevented by the timely use of antibiotics.

Table 2.8 reveals the contemporaneous impact that noneconomic damages caps have on health outcomes related to antibiotic use. As we can see from the table, noneconomic damages caps are not causing an increase in hospital discharges for peritonsillar abscess, rheumatic fever, septicemia, pneumonia, and meningitis, even though doctors prescribe fewer antibiotic when states adopt caps. We do, however, observe a statistically significant increase in hospital discharges for mastoiditis after a noneconomic damages cap is enacted. While the effect size is small in absolute terms (0.0013 percentage points), it represents a 26-percent increase over the baseline estimate of 35,107 hospital discharges for mastoiditis that occur in the U.S. in the period from 1993 to 2011.

Given that some complications of conditions that can be treated with antibiotics in primary care may only manifest after a period of several weeks, it is important to look not only at the contemporaneous impact of noneconomic damages caps but also at their impact over time. Table 2.9 shows how caps on noneconomic damages affect health outcomes related to antibiotic use over time. While some of the coefficients are statistically significant, there is no clear pattern that would allow us to conclude that the fewer antibiotic prescriptions after noneconomic damages cap reforms translate into more hospitalizations.[31]

In sum, the health outcome results support the notion that marginal antibiotics are used

[31]Note that Table 2.9 tests multiple hypotheses. Just by chance, some of the coefficients therefore have to be statistically significant.

Table 2.9: Impact of noneconomic damages caps on health outcomes (II)

	Peritonsillar abscess	Rheumatic fever	Mastoiditis	Septicemia	Pneumonia	Meningitis
CAP_t	-31.95**	5.98	8.04	0.04	-1.94	-16.46*
	(14.40)	(34.73)	(46.80)	(3.99)	(2.82)	(8.49)
CAP_{t-1}	10.51	-15.51	23.03	3.73	3.80*	-11.85
	(17.12)	(41.82)	(37.07)	(2.34)	(2.04)	(10.72)
CAP_{t-2}	18.41	-9.76	-43.20*	-1.59	4.50	18.59
	(15.35)	(47.86)	(24.45)	(3.53)	(3.01)	(13.49)
CAP_{t-3}	13.84	10.86	40.19**	1.88	-2.83	-0.91
	(12.54)	(18.63)	(17.55)	(5.18)	2.05	(12.36)
R^2	0.00	0.00	0.00	0.01	0.02	0.00
N			98,275,213			

Notes: Table reports results from OLS estimation of equation (2.4), where three months of lags of the cap indicator also enter into the regression model. The coefficients on the cap on noneconomic damages and the corresponding standard errors, which are shown in parentheses, are divided by the mean of the dependent variable and multiplied by 100. Standard errors are adjusted for clustering at the state level. * p<0.1, ** p<0.05, *** p<0.01.

for defensive reasons and have little or no health benefits. Even though there is a statistically significant increase in the number of discharges with the primary diagnosis mastoiditis, the cost of these additional discharges is likely to be inferior to the cost savings through a reduction in antibiotic prescriptions.[32] The empirical findings thus confirm the prediction of the theoretical model that liability-induced antibiotics are socially wasteful when the amount of antibiotic prescriptions decreases after the introduction of noneconomic damages caps.

2.7 Conclusion

By holding healthcare professionals accountable, the medical malpractice system is supposed to improve patient outcomes and deter healthcare providers from providing too little care. An unintended consequence of the malpractice system is that it can induce healthcare professionals to provide too much care, a phenomenon known as defensive medicine.

This paper shows that antibiotics are used as defensive medicine. Noneconomic damages cap reforms affect the likelihood with which doctors prescribe antibiotics but do not affect hospital stays for conditions that can be prevented through the timely use of antibiotics, with the possible exception of mastoiditis. A theoretical model complements the empirical analysis and predicts likewise that antibiotics are used defensively. Considering the large burden of

[32] Take into consideration that there are only about 2,000 mastoiditis hospitalizations per year but almost 120 million ambulatory care visits in which doctors prescribe antibiotics.

antibiotic resistance, policymakers may contemplate adopting liability-reducing tort reforms to decrease the inappropriate use of antibiotics. The results from this paper suggest that if all states adopted a cap on noneconomic damages, this would reduce the number of ambulatory care visits that result in the patient receiving a prescription for antibiotics by approximately 3.2 million.

Appendices

2.A Classification of Drugs

The NAMCS questionnaire asks physicians to record information on up to eight drugs (five drugs in 1993 and 1994, six drugs from 1995 to 2002). The recorded verbatim responses are assigned a unique five-digit code according to a classification scheme developed by the NCHS. I have classified drugs using the NCHS Ambulatory Care Drug Database System,[33] which is based on the Lexicon Plus classification of drugs by Cerner Multum Inc.

Table 2.10: Classification of antibiotics based on spectrum of activity

Spectrum	Antibiotics
Narrow	1st- and 2nd-generation cephalosporins, aztreonames, colistines, daptomycin, linezolides, metronidazoles, novobiocins, polymyxin, narrow-spectrum penicillins, tetracyclines, sulfonamides, glycopeptides
Broad	carbapenems, 3rd- and 4th-generation cephalosporins, macrolides, bacitracin, chloramphenicol, rifaximin, furazolidone, aminoglycosides, pentamidines, methenamines, fosfomycins, nitrofurantoins, quinolones, broad-spectrum penicillins, glycylcyclines

The following subcategories of anti-infective drugs are classified as antibiotics: carbapenems, cephalosporins, macrolide derivatives, penicillins, quinolones, sulfonamides, tetracyclines, urinary anti-infectives, aminoglycosides, lincomycin derivatives, glycylcyclines, glycopeptide antibiotics, and miscellaneous antibiotics. Following the medical literature, in particular Shapiro *et al.* (2014), I have further divided antibiotics into broad- and narrow-spectrum antibiotics as shown in Table 2.10. For a small number of cases (117 out of 546,990 of visits), it was not possible to assign a spectrum of activity to the antibiotic that was prescribed during the visit.[34]

[33] http://www.cdc.gov/nchs/ahcd/ahcd_database.htm (last accessed June 3, 2016).

[34] The following NCHS drug entry codes could not be classified: empiric antibiotics, SBE prophylaxis, antimicrobial, endomycin, sulfametin, bacteriostatic, IV antibiotics, antifungal agent, antiinfective agent, antitubercular agent, tuberculin medication, ringworm medicine, antibacterial agent.

Table 2.11: Antibiotics substitutes: Respiratory agents

#	Antihistamines	Antitussives	Decongestants	Expectorants	URC
1	Claritin	Hydrocodone	Sudafed	Robitussin	Entex
2	Zyrtec	Tessalon Perle	Dimetapp	Mucinex	Allegra D
3	Allegra	Codeine	Neo-synephrine	Humibid	Phenergan+Codeine
4	Benadryl	Cough syrup	Decongestant	Guaifenesin	Tussionex
5	Phenergan	Delsym	Phenylephrine	Cough formula	Rondec-DM syrup
6	Seldane	Cheratussin	Mydfrin	Organidin	Rynatan
7	Atarax	Tessalon	Pseudoephedrine	Duratuss G	Robitussin-DM syrup
8	Loratadine	Benzonatate	Ayr Nasal Gel	Humibid LA	Robitussin A-C syrup
9	Clarinex	Dextromethorphan	AK Dilate	Liquibid	Duratuss
10	Hydroxyzine	Benzonatate	Nasal decongestant	Tussin	Claritin D

Table shows the top 10 drugs in terms of the number of prescriptions in the NAMCS data (brand-name and generic versions accounted for separately) for five classes of respiratory agents.

Considering the drugs that are commonly prescribed together with antibiotics and the drugs that are prescribed for conditions for which antibiotics are commonly prescribed, I have identified the following respiratory agents as possible substitutes for antibiotics: antihistamines, antitussives, decongestants, expectorants, and upper respiratory combinations. For each of these classes, I have identified the top 10 drugs in terms of the number of prescriptions in the NAMCS data (shown in Table 2.11) and created indicators based on whether one or more of the top 10 drugs was prescribed during the visit. In addition to the aforementioned respiratory agents, I consider three common antiinflammatory agents – Tylenol, Advil, and Aspirin (both brand-name and generic version of each) – as potential substitutes for antibiotics.

2.B Bad control tests

Table 2.12: Bad control tests

	NAMCS	NIS
Patient age	-1.3992***	-0.5484
	(0.4580)	(0.3559)
Patient female	0.0012	0.0002
	(0.0080)	(0.0013)
Patient white	-0.0079	0.0081
	(0.0113)	(0.0122)
Patient black	0.0078	0.0013
	(0.0088)	(0.0090)
Patient latino	0.0084	-0.0020
	(0.0069)	(0.0045)
Private insurance	0.0197**	0.0094
	(0.0082)	(0.0083)
Medicare	-0.0125**	-0.0086
	(0.0058)	(0.0077)
Medicaid	0.0088	-0.0003
	(0.0059)	(0.0053)
MD (vs. DO)	0.0018	—
	(0.0065)	
Primary care physician (vs. specialist)	0.0192	—
	(0.0140)	
Physician age	-0.1694	—
	(1.7600)	
Physician female	-0.0080	—
	(0.0138)	
Practice/hospital in MSA	-0.0357	0.0105
	(0.0276)	(0.0265)

Notes: Table reports results from estimations of equation (2.4), where each cell reports the results from a separate regression and the control vectors X and Z do not enter into the regressions. Rows indicate the dependent variable. Columns 1 and 2, respectively, report bad control tests for the covariates from the NAMCS and NIS data. Standard errors adjusted for clustering at the state level in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

3 Tort Reform and the Length of Physician Office Visits

3.1 Introduction

Tort reform remains a heavily debated topic in the United States.[35] Advocates of tort reform, such as the American Tort Reform Association, argue that it improves the functioning of the civil justice system, reduces the practice of defensive medicine,[36] and helps to curb the growth in healthcare expenditures. Opponents of tort reform, which include trial lawyer associations and consumer groups, argue that it harms patients by denying them fair compensation for injuries, reduces incentives for physicians to provide adequate levels of care, and leads to modest expected savings.

This paper contributes to the debate on tort reform by providing the first direct evidence on how tort reform affects the time that physicians spend with patients. There is a close connection between the length of physician office visits and the medical malpractice system: patients who feel rushed and poorly understood are more likely to file a malpractice claim (Hickson *et al.* 1992), and physicians with greater exposure to malpractice claims devote, on average, less to time their patients (Hickson *et al.* 1994, Levinson *et al.* 1997). To determine whether physicians adjust the time spent with patients in response to tort reforms, I use data from the National Medical Care Ambulatory Survey (NAMCS) on more than 500,000 physician office visits that took place between 1993 and 2011. Exploiting legislative variation across states and over time in a difference-in-differences framework, I present estimates of the causal effects of four commonly adopted tort reforms – caps on noneconomic damages, caps on punitive damages, reforms of the joint-and-several liability rule, and reforms of the collateral-source rule – on the length of office visits in U.S. ambulatory care.

Results suggest that doctors do not adjust the time they devote to patients in response to caps on noneconomic and punitive damages and reforms of the joint-and-several liability rule. Results are less clear regarding reforms of the collateral-source rule, which, according to some specifications, reduce the length of office visits. These findings hold not only for the average patient and physician but also for various patient and physician subgroups, such as patients with private health insurance and physicians in high-risk specialties. Among the most likely explanation for why physicians do not adjust the length of office visits are ethical and financial constraints.

The remainder of the paper continues as follows. Section 3.2 provides background information and references to the literatures on liability for medical malpractice and tort reform. Section 3.3 describes the data and provides summary statistics of the analysis sample. Section

[35] Studdert *et al.* (2004) provide an excellent account of the U.S. medical malpractice system and the controversies surrounding tort reform.

[36] Defensive medicine is commonly defined as care that physicians order to avoid lawsuits but for which social cost exceeds social benefits.

3.4 lays out the empirical strategy. Section 3.5 presents the results. Section 3.6 discusses why physicians may not adjust the length of office visits in response to tort reforms. Section 3.7 concludes.

3.2 Background

3.2.1 Liability for Medical Malpractice

Patients who received care in the U.S. can sue healthcare providers for medical malpractice according to the terms set out in the tort law. Liability for medical malpractice is generally based on the negligence standard. This means that patients, in order to get compensated, have to establish that the care they received and suffered harm from was performed negligently and fell below the standard of care that is expected from physicians in the community.

Lawsuits for medical malpractice are a rather common phenomenom in the U.S., at least in comparison to other countries. Jena *et al.* (2011) estimate that 7.4% of all physicians are sued in a given year, and that the lifetime risk of being sued is north of 75%. Jena *et al.* (2011) also show that the proportion of physicians facing a malpractice claim varies widely across physician specialties: more than 15% of surgeons are sued for medical malpractice in a given year compared to 3.1% of pediatricians. Most physicians are fully insured against any direct financial consequences from medical malpractice claims (Danzon 2000, Zeiler *et al.* 2007). However, there are considerable, uninsurable nonmonetary cost associated with being sued for medical malpractice, which include the time that is required to defend a claim and damages to reputation. For this reason, it is understandable that physicians concerns about malpractice risks are pervasive. Carrier *et al.* (2010), for example, report that more than 60 percent of physicians feel threatened in their day-to-day practice by potential malpractice litigiation against them.

In theory, liability for medical malpractice should align the interests of physicians and other healthcare providers with those of patients. Because it punishes the provision of too little care, liability for medical malpractice should encourage physicians to exert adequate levels of effort and reduce adverse health outcomes.[37] An unintended consequence of the medical malpractice system is that physicians sometimes provide treatments with social cost above social benefits because they fear legal repercussions. Such behavior is known as defensive medicine and has received considerable interest in the literature.[38]

[37] Iizuka (2013) provides evidence that higher malpractice pressure indeed reduces the occurrence of preventable medical complications.

[38] Doctors have been found to practice defensive medicine by increasing the treatment intensity for patients with heart attack (Kessler and McClellan 1996, Avraham and Schanzenbach 2015), ordering more imaging services (Baicker *et al.* 2007), and prescribing more antibiotics (Panthöfer 2016). The empirical evidence on the use of Cesarean sections, which are a usual suspect of defensive behavior by physicians, is mixed (compare, for example, Shurtz 2013 with Currie and MacLeod 2008).

There is surprisingly little evidence on how the medical malpractice system affects the time that physicians and other healthcare providers devote to their patients. Given that visit length is a predictor of malpractice claim frequency (Levinson *et al.* 1997), one may expect that physicians adjust the time they spend with patients in response to a change in liability pressure. Many of the physicians who participated in the surveys of Reynolds *et al.* (1987) and Lawthers *et al.* (1992) report that they increase the time they spend with patients when they feel pressured. Danzon *et al.* (1990) mention a positive correlation between office visit lengths and liability pressure but do not provide any estimates. In this paper, I provide the first direct evidence on how tort reforms affect the time physicians spend with patients, using data on physician office visits over a 19-year period.

3.2.2 Tort Reform

The U.S. tort law is organized at the state level. Partially in response to several so-called malpractice crises, the state tort laws have undergone three major periods of reform (in the mid 1970s, the mid 1980s, and the early 2000s). The following four reforms are the most frequently adapted over the period from 1993 to 2011 and the focus of this study.

1. Caps on noneconomic damages: Noneconomic damages are awarded for nonpecuniary harms – such as pain and suffering, emotional distress, and loss of consortium – and account for about 50% of the typical medical malpractice award (Hyman *et al.* 2009). Caps on noneconomic damages unambiguously lower the malpractice pressure that physicians experience: they reduce expected awards and, therefore, lower the incentives for patients to file a malpractice claim and for trial lawyers – who generally work on a contigency fee basis – to take up a patient's case.[39]

2. Caps on punitive damages: Punitive damages are awarded to plaintiffs, but the intention behind them is to punish tortfeasors and deter misconduct. Punitive damages are seldom awarded in medical malpractice cases because they are typically restricted to the most severe cases of misconduct, which involve intent, actual malice, or gross negligence. It is therefore not surprising that caps on punitive damages are generally not associated with jury awards, settlement amounts, and claim frequency in medical malpractice cases (see the reviews by Holtz-Eakin 2004 and Mello 2006).

3. Modifications of the collateral-source rule (CSR): The common law CSR prohibits the admission of evidence that the plaintiff has been compensated from sources other than the defendant, such as the plaintiff's health insurance, effectively allowing plaintiffs to

[39]For empirical evidence on the effect of noneconomic damages caps on various measures of malpractice pressure, see, for example, Hyman *et al.* 2009, Avraham 2007, Paik *et al.* 2013, and Thorpe 2004.

be compensated twice for the same injury. Modifications of the common law CSR generally reduce expected awards by admitting evidence that plaintiffs have been compensated by third parties and should therefore, at least theoretically, also reduce incentives for plaintiffs to file lawsuits. In practice, however, there is no clear association between measures of malpractice pressure and reforms of the CSR (Holtz-Eakin 2004, Mello 2006).

4. Modifications of the joint-and-several liability (JSL) rule: The common law JSL rule allows plaintiffs to recover damages from multiple defendants collectively or from each defendant individually, regardless of the shares of liability that are apportioned to the defendants. Modifications of the common law JSL rule generally restrict the way in which plaintiffs can sue the involved parties in a multi-party malpractice case. Currie and MacLeod (2008) argue that such modifications put more liability pressure on physicians because they align more closely the risk of liability with the physician's level of care. However, Currie and MacLeod also mention that JSL reforms lower the incentives for patients to initiate a malpractice claim. On balance, it is not clear – neither theoretically nor in practice – whether modifications of the JSL rule lead to doctors experiencing more or less malpractice pressure.

3.3 Data, Sample, and Descriptive Statistics

The empirical analysis is based on data from the National Ambulatory Medical Care Survey. NAMCS is a nationally representative survey of visits to non-federal employed office-based physicians in the U.S., excluding anesthesiologists, pathologists, and radiologists. Each of the about 1,200 physicians who participate annually in the survey is randomly assigned to reporting period of one week. During this week, data are collected for a systematic random sample of about 25 patients. Physicians and patients may participate in multiple survey years, but it is not possible to identify longitudinal linkages. For each patient visit, the NAMCS records hold the patient's symptoms, the physician's diagnosis according to the ICD-9-CM, treatments and medications ordered or provided, and the duration of the visit (top-coded at 240 minutes).

Table 3.1 shows descriptive statistics for the sample, which consists of all visits with nonzero duration. Observations with a visit duration of zero minutes (4.3% of all observations) are not comparable to nonzero duration visits and therefore omitted from the sample.[40] The sample period runs from 1993 to 2011, and the sample includes a total of 523,488 visits. Figure 3.1 shows that there is bunching of the visit duration at round numbers, part of which may be attributed to measurement error. The mean visit duration is slightly above 20 minutes,

[40] Visits with a duration of zero minutes correspond to, for example, a nurse giving an inoculation.

Table 3.1: Descriptive statistics

	Mean	SD	25%	50%	75%	99%	N
Visit duration	20.82	13.80	15	15	25	60	523,436
Age	45.73	24.47	28	48	66	89	523,488
Female	0.57	0.49					523,488
White	0.77	0.42					491,782
Black	0.09	0.29					491,782
Latino	0.10	0.30					491,782
Private insurance	0.53	0.50					506,980
Medicare	0.23	0.42					506,980
Medicaid	0.11	0.32					506,980
MD	0.92	0.28					523,488
MSA	0.86	0.35					523,488

Notes: Table reports descriptive statistics for office visits with nonzero duration. Percentages indicate percentiles. Age, gender, race, and ethnicity are patient characteristics. MD indicates whether physician has a Doctor of Medicine (MD) as opposed to a Doctor of Osteopathic Medicine (DO). MSA indicates whether practice is located in a MSA.

Figure 3.1: Histogram of visit duration

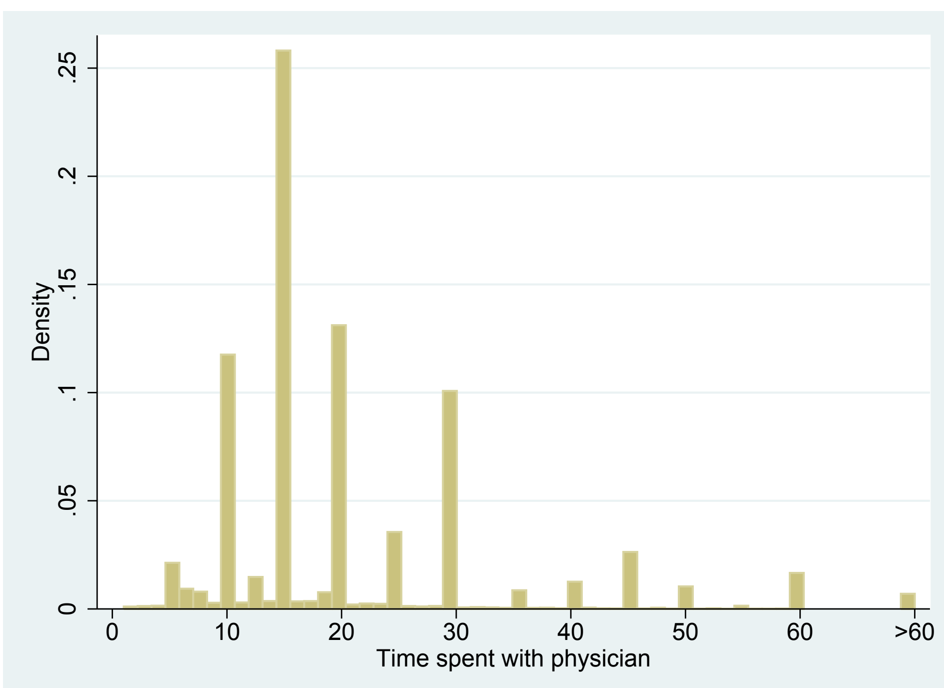


Table 3.2: Tort reforms, 1993-2011

	Law enacted				Law repealed			
Cap on non-economic damages	IL	03/09/95	ND	08/01/95*	IL	12/18/97	OH	02/25/98
	MT	10/01/95*	OH	01/27/97	OR	07/15/99	WI	07/14/05*
	NV	10/01/02*	MS	01/01/03*	IL	02/04/10*	GA	03/22/10*
	OK	07/01/03*	TX	09/01/03*				
	GA	02/16/05*	SC	07/01/05*				
	IL	08/24/05*	WI	04/06/06*				
	NC	10/01/11*	TN	10/01/11				
Joint-and-several liability reform	IL	03/09/95	WI	05/17/95	IL	12/18/97	OH	02/25/98
	OH	01/27/97	PA	08/18/02	PA	07/26/05		
	NV	10/01/02*	AR	03/25/03				
	OH	04/09/03	GA	02/16/05				
	SC	07/01/05	PA	06/28/11				
	OK	11/01/11						
Cap on punitive damages	ND	04/30/93	IN	06/30/95	AL	06/25/93	OH	08/25/98
	OK	08/25/95	NJ	10/27/95	AR	12/08/11		
	NC	01/01/96	PA	01/25/97*				
	OH	01/27/97	AK	08/07/97				
	AL	06/07/99	MS	01/01/03				
	AR	03/25/03	ID	07/01/03				
	MT	10/01/03	OH	01/06/05				
	MT	06/27/05	TN	10/01/11				
Collateral-source rule reform	WI	05/25/95*	OH	02/25/98*	KS	04/16/93	KY	01/19/95
	AL	09/22/00	PA	03/20/02*	AL	07/12/96	OH	01/27/97*
	WV	03/08/03*	OK	07/01/03*				

Notes: Asterisk indicates that the law applies/applied only to medical malpractice rather than to all torts.

and 99 percent of the visits last less than one hour. Throughout the sample period, there is no trend over time in the mean visit duration.

Geographic information in the public-use NAMCS data is limited and restricted to identifiers indicating census region and MSA status. I obtained access to restricted-use NAMCS data at the Research Data Center of the National Center for Health Statistics (NCHS). Using this data, I could identify the county and state in which physician practices are located and assign the corresponding state tort laws – which are based on information from Ronen Avraham's Database of State Tort Law Reforms (Avraham 2014), the state law data provided in an appendix to Currie and MacLeod (2008), the American Tort Reform Association, and the state codes – to the observations. I cover the four reforms discussed earlier and the years from 1992 to 2012 on a monthly basis, where the years 1992 and 2012 are covered to allow for the inclusion of reform lags and leads of up to one year. Following Frakes (2012), I say that noneconomic damages and punitive damages are capped if a state caps the total amount of damages that can be awarded. Table 3.2 lists the reforms that have taken place over the sample period.

3.4 Empirical Strategy

The empirical strategy is centered around the state tort reforms that are listed in Table 3.2. To determine the causal effect of each of the four reforms, I adopt a difference-in-differences specification, which relies on the assumption that states that adopt a given tort reform would, if they had not adopted the reform, experience the same trend in the length of office visits as states that do not adopt the reform. The empirical specification for the length of office visits is the following:

$$\text{TIMEMD}_{ist} = \alpha + \beta\text{LAW}_{st} + \gamma X_{ist} + \theta_t + \phi_s + \varepsilon_{ist}. \tag{3.1}$$

TIMEMD_{ist} is the recorded visit duration, where the subscripts i, s, and t stand for, respectively, a visit, a state, and a year-month combination. LAW_{st} is a vector of dummies that indicate whether state s imposes a cap on noneconomic damages, a cap on punitive damages, modifications of the joint-and-several liability rule, and modifications of the collateral-source rule in period t. X_{ist} is a vector of visit-level controls. In its most basic form, this vector includes dummies for patient age (<5, 5-17, 18-44, 45-64, 65-79, 80+), patient gender, patient race and ethnicity (white, black, latino, other), health insurance (private, Medicare, Medicaid, other), physician degree (MD, DO), physician specialty (fourteen categories), physician age (<35, 35-54, 55+), physician gender, and practice (MSA, non-MSA). In some regressions, I additionally control for the patient's reason for visit following the NCHS reason for visit classification (forty-three categories) or the physician's diagnosis based on the first subcategory of the ICD-9-CM classification (159 categories). θ_t indicates a year-month combination, ϕ_s indicates a state, and ε_{ist} is the error term. Following Bertrand *et al.* (2004), I report standard errors that are clustered at the state level.

I extend the baseline analysis in two directions. First, I study which doctors and patients are particularly affected by tort reforms. To this end, I estimate models that include interaction terms between the law indicators and variables such as the patient's type of health insurance and the physician's specialty, which have previously been identified as sources of heterogeneity in the malpractice literature. Second, I conduct a variety of sensitivity analyses in order to assess whether the results are robust to several potential threats and whether the identification strategy is valid.

Table 3.3: Impact of tort reforms on length of office visits

	No controls	Basic controls	Basic controls and reason for visit	Basic controls and physician's diagnosis
Cap on noneconomic damages	-0.55	-0.13	-0.12	-0.19
	(0.33)	(0.30)	(0.30)	(0.30)
Joint-and-several liability reform	-0.10	-0.57	-0.63	-0.56
	(0.76)	(0.72)	(0.69)	(0.70)
Cap on punitive damages	0.10	0.11	0.14	0.15
	(0.47)	(0.48)	(0.49)	(0.48)
Collateral-source rule reform	-0.62	-0.47	-0.56	-0.47
	(0.44)	(0.53)	(0.53)	(0.53)
R^2	0.02	0.15	0.17	0.17
N	523,488	462,787	457,533	456,609

Notes: Table reports results from OLS estimation of equation (3.1). Standard errors adjusted for clustering at the state level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

3.5 Results

Table 3.3 shows how the four tort reforms under study affect the length of office visits. None of the reform effects is statistically significant at the 90-percent confidence level in the baseline model (Column 2), suggesting that tort reforms do not affect how much time physicians devote to their patients. Controlling for the patient's reason for visit or the physician's diagnosis increases the predictive power of the regression model but does not result in statistically significant reform effects. Similarly, not controlling for age, gender, and the other basic controls listed in Section 3.4 leads to a drop in the R-squared of the regression but does not change the fact that none of the tort reforms has a statistically significant effect on the duration of office visits at conventional levels of confidence. Across the four models, the coefficient estimates suggest that tort reforms do not change the length of office visits by more than half a minute (2.5% of the average visit length). The 95-percent confidence intervals exclude the possibility that any of the four tort reforms changes visit durations by more than two minutes (10% of the average visit length). In sum, Table 3.3 presents evidence suggesting that tort reforms do not affect the length of office visits in U.S. ambulatory care, both in statistical terms and judging from the magnitude of the coefficients.

But what if tort reforms affect only certain patients or physicians? The previous results resemble average effects across all physicians and patients, which may not tell the whole story. For example, the malpractice literature has highlighted that doctors are more sensitive about Medicaid and uninsured patients, and that different physician specialties are confronted with substantially different odds of malpractice lawsuits. Tables 3.4 demonstrates that health in-

Table 3.4: Interaction between tort reforms and patient's type of health insurance

	Law	Law × Private	Law × Medicare	Law × Medicaid	Law × Other
Cap on noneconomic damages	-0.21	0.00	0.15	0.15	0.08
	(0.32)	—	(0.19)	(0.21)	(0.36)
Joint-and-several liability reform	-0.56	0.00	-0.07	-0.02	0.19
	(0.72)	—	(0.20)	(0.21)	(0.38)
Cap on punitive damages	0.28	0.00	-0.37*	-0.03	-0.62
	(0.49)	—	(0.19)	(0.26)	(0.40)
Collateral-source rule reform	-0.58	0.00	0.03	0.10	0.69*
	(0.56)	—	(0.21)	(0.24)	(0.35)
R^2			0.15		
N			462,787		

Notes: Table reports results from OLS estimation of equation (3.1) augmented for interaction terms between indicators of the laws and the patient's type of health insurance. The dependent variable is the length of office visits. The reference category consists of the privately insured patients. Standard errors adjusted for clustering at the state level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

surance status does not interact with the four tort reforms considered in this paper. Out of the twelve interaction terms in Table 3.4, two are significant at the 90-percent level of confidence. However, in both cases, the coefficient on the interaction term and the coefficient on the law itself sum up to zero, suggesting that the law does not have a statistically significant impact on the subgroup. Table 3.5 paints a similar picture but with respect to physician specialties. Surgeons, gynecologists, and obstetricians, who face the highest odds of malpractice lawsuits, do not consistently depart in their response to tort reforms from all other specialties.[41] Likewise, physicians in low-risk specialties such as general practice and pediatrics do not react differently to tort reforms in comparison to their peers. The same applies to most other observable patient and physician characteristics, including age, gender, medical degree (MD/DO), practice type (solo/group), and type of healthcare (primary care/specialist care).[42]

As with any difference-in-differences strategy, the previous results hinge on the assumption that the interventions – the four tort reforms – are exogenous and orthogonal to trends in the outcome variable in the treatment and control states. Table 3.6 presents the results of four different models aimed at testing the identifying assumption. The first model includes indicators that equal one in the six months before the tort reforms are implemented. As

[41]However, we can notice that orthopedic surgeons do statistically significantly increase the length of office visits after caps on punitive damages. For general surgeons and reforms of the JSL rule, we observe a statistically different response from all other specialties, but the interaction term and the coefficient on the JSL rule itself roughly sum up to zero, suggesting that general surgeons do not respond to JSL reforms.

[42]Results are available upon request.

Table 3.5: Impact of tort reforms on physician specialties

	General practitioners		Pediatricians		Ob/gyns		General surgeons		Orthopedic surgeons	
	Law	Law × GP	Law	Law × PD	Law	Law × OB	Law	Law × GS	Law	Law × OS
Cap on noneconomic damages	-0.17	0.18	-0.12	-0.26	-0.15	0.28	-0.10	-0.50	-0.15	0.41
	(0.33)	(0.42)	(0.31)	(0.41)	(0.31)	(0.36)	(0.30)	(0.53)	(0.31)	(0.49)
Joint-and-several liability reform	-0.52	-0.23	-0.57	0.05	-0.57	0.05	-0.64	1.05**	-0.59	0.32
	(0.71)	(0.34)	(0.72)	(0.45)	(0.71)	(0.36)	(0.70)	(0.42)	(0.72)	(0.48)
Cap on punitive damages	0.06	0.31	0.06	0.70	0.11	0.13	0.08	0.39	0.04	1.10**
	(0.48)	(0.37)	(0.48)	(0.45)	(0.49)	(0.36)	(0.48)	(0.41)	(0.49)	(0.46)
Collateral-source rule reform	-0.45	-0.20	-0.44	-0.39	-0.44	-0.57	-0.54	0.54	-0.51	0.62
	(0.53)	(0.35)	(0.52)	(0.37)	(0.53)	(0.36)	(0.53)	(0.47)	(0.53)	(0.48)
R^2	0.15		0.15		0.15		0.15		0.15	
N	462,787		462,787		462,787		462,787		462,787	

Notes: Table reports results from OLS estimation of equation (3.1) augmented for interaction terms between indicators of the laws and physician specialties. The dependent variable is the length of office visits. For each of the five specialties, the reference category consists of all other specialties. Standard errors adjusted for clustering at the state level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.6: Tests for legislative endogeneity

	Six-month lead of reforms	Only reforms turning off	Excluding reforms specific to medical malpractice	State-specific time trends
Cap on noneconomic damages	-0.64	-0.05	0.15	0.15
	(0.77)	(0.31)	(0.55)	(0.63)
Joint-and-several liability reform	-0.55	-0.27	-0.70	0.59
	(0.61)	(0.47)	(0.67)	(0.67)
Cap on punitive damages	1.45	-0.19	0.24	-0.41
	(0.89)	(0.66)	(0.61)	(0.47)
Collateral-source rule reform	2.04	1.71**	-1.75*	-1.21**
	(1.40)	(0.78)	(1.02)	(0.53)
R^2	0.15	0.15	0.15	0.14
N	462,787	462,787	462,787	482,452

Notes: Table reports results from OLS estimation of equation (3.1). Column 1 reports coefficients on dummies that equal one in the six months before the tort reforms are enacted. Column 2 reports coefficients on dummies that equal one as long as the tort reforms have been turned off. Column 3 reports coefficients on tort reform indicators that are not affected by reforms that are specific to medical malpractice. Column 4 reports coefficients on tort reform indicators from a model that includes state-specific time trends and visits with zero duration. Standard errors adjusted for clustering at the state level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

we can see, states that adopt tort reforms and states that do not adopt tort reforms do not feature statistically different office visit lengths in the six months before the introduction of the reforms. The second model includes only tort reforms that are turned off, which include, for example, reforms where a damages cap is repealed. The rationale behind this second model is that tort reforms are almost exclusively turned off because the respective state supreme court ruled that the reform violated the state constitution. For this reason, tort reforms that are being turned off are plausibly exogenous to trends in medical care. As we can see, whether we include all reforms or only reforms that are turned off makes no difference for both kinds of caps on damages and reforms of the JSL rule. However, we observe a statistically significant and positive effect of CSR reform repeals on visit durations. The third model includes only tort reforms that apply not only to medical malpractice cases but also to product liability cases, auto accidents, etc. These reforms are arguably less susceptible to legislative endogeneity than reforms that are specifically aimed at medical malpractice cases. The results of the third model mirror those of the second one: caps on noneconomic and punitive damages and JSL reforms have no impact on the length of office visits but CSR reforms reduce the length of office visits.[43] The fourth and final test of legislative endogeneity incorporates state-specific linear time trends in the regression model. After controlling for state-specific time trends, CSR reforms reduce the length of office visits and the three remaining reforms continue to have no statistically significant impact. Taken together, the four tests of legislative endogeneity suggest that the identifying assumption is valid for damages caps and reforms of the JSL rule, but that it may not hold for CSR reforms. As discussed before, CSR reforms should, at least theoretically, lead to a reduction in malpractice pressure. Physician therefore act in accordance with economic incentives if they reduce visit durations after CSR reforms. Why physicians would only react to CSR reforms and not to other liability-reducing tort reforms, such as caps on noneconomic damages, is not clear.

Table 3.7 addresses several threats that could affect the empirical findings. One such threat is the simultaneous passing of tort reforms. If states adopt several tort reforms at once, which some states do (compare Table 3.2), it may be hard to separately estimate the effect of each the reforms. To address this issue, I have estimated four separate models, one for each of the reforms. The results of these four models, which are shown in Column 1, do not differ markedly from the baseline model. I have also collapsed the two indicators for caps on noneconomic damages and caps on punitive damages into one indicator for any kind of damages caps. This composite indicator has no statistically significant impact on the length of office visits either. Another threat concerns the bunching in the visit duration at round numbers, which we have observed in Figure 3.1. While doctor visits are frequently scheduled to last for fifteen (or ten or twenty) minutes, the actual visit duration is perhaps more uniformly

[43]To some extent, this result could be anticipated as the CSR reforms that are being turned off and the CSR reforms that are not specific to medical malpractice cases are almost congruent (compare Table 3.2).

Table 3.7: Robustness checks

	Each reform separately	Any kind of cap	Binary dependent variable	Excluding imputed	Excluding visits >60 min	Including 0-min visits
Cap on non-economic damages	-0.30		0.01	-0.38	-0.02	0.06
	(0.33)		(0.01)	(0.36)	(0.27)	(0.37)
Joint-and-several liability reform	-0.64		(0.02)	-0.71	-0.61	-0.42
	(0.62)		(0.03)	(0.79)	(0.79)	(0.83)
Cap on punitive damages	-0.15		-0.00	-0.02	0.11	0.11
	(0.37)		(0.03)	(0.51)	(0.48)	(0.46)
Collateral-source rule reform	-0.53		0.02	-0.83	-0.48	-0.61
	(0.40)		(0.02)	(0.55)	(0.54)	(0.52)
Any cap		-0.03				
		(0.36)				
R^2		0.15	0.09	0.16	0.20	0.14
N		462,787	462,787	366,211	458,730	482,452

Notes: Table reports results from OLS estimation of equation (3.1). Column 1 reports results from four different regressions, where all laws other than the one corresponding to the row name are excluded from the regression model. Column 2 reports from a model that includes only one law dummy, which indicates any kind of damages caps. In Column 3, the dependent variable is a dummy indicating whether the visit lasted longer than 15 minutes. Column 4 excludes observations with imputed values. Column 5 excludes visits lasting longer than one hour. Column 6 includes visits with zero duration. Standard errors adjusted for clustering at the state level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

distributed than the recorded visit duration, which may suffer from measurement error. However, if this measurement error is not correlated with the passing of tort reforms, which seems likely, then it poses no threat to the consistent estimation of the tort reform effects but leads to inflated standard errors. Given what we have concluded about the magnitude of the coefficient estimates, it appears unlikely that inflated standard errors due to measurement error would prevent us from detecting significant effects of tort reforms. Moreover, none of the four tort reforms has a statistically significant impact on an alternative, binary dependent variable, which equals one if one if the office visit lasted longer than 15 minutes (the median visit length) and which should, to some extent, be less affected by measurement error. The models corresponding to Columns 4 to 6 in Table 3.7 deal with imputed values,[44] visits that last longer than one hour, and visits with zero duration. None of these issues seems to affect the conclusion that tort reforms have no impact on the duration of office visits.

3.6 Discussion

In this section, I discuss several potential explanations for why physicians would not adjust the length of office visits in response to tort reforms. One of these explanations could be that physicians do not notice, or pay only little attention, to tort reforms and their impact on the liability climate in the state. While Carrier *et al.* (2010) find that physicians' fear of malpractice is only weakly correlated with the prevailing malpractice laws, this does not necessarily mean that tort reforms do not change physicians' perception of malpractice pressure. Moreover, the argument that physicians do not care about tort reforms seems to be at odds with numerous studies that find an effect of tort reforms on treatment and medication choices (see, for example, Kessler and McClellan 1996 and Currie and MacLeod 2008). All in all, it seems unlikely that physicians do not take tort reforms into account.

It could also be that physicians adjust the length of office visits in response to tort reforms for different patients differently. Plausibly, physicians want to spend more time with high-risk patients after an increase in liability pressure. To make up for the increased time spent on high-risk patients, physicians may handle low-risk patients more quickly, leaving the average visit length unchanged. Tort reforms could also lead to changes in the patient mix that physicians treat. If physicians are less willing to take up high-risk patients after an increase in liability pressure, we may find no change in visit durations but for a patient population that is significantly healthier after the reform. This would suggest that physicians, after an increase in liability pressure, spend more time on patients with the same risk profile. Similarly, physicians could also adjust the total time spent on a given patient by scheduling more (or less, for that matter) visits for this patient and we would not observe such behavior in the data. I will

[44] The following variables are imputed by the NCHS if the information is missing on the patient record form: age, ethnicity, race, gender, time spent with physician, visit date.

explore these explanations in more detail in future research.

Two alternative explanations for the absence of an effect of tort reforms on office visit durations are related to the legal burden of proof of medical malpractice. As Frakes and Jena (2016) have pointed out, tort reforms affect physicians in different areas of a state differently, because of varying local standards, which could imply that the effects of tort reform cancel out at the state level. However, it seems unlikely that physicians in the same state spend vastly different amounts of time on patients, which would give rise to varying local standards. Alternatively, it could be that the time spend with patients is not always verifiable in court, as opposed to the use of procedures and administration of medication, which would lead physicians to adjust their behavior only along the latter margins. However, even if the visit duration is not verifiable in court, spending more time with patients should lead to a more precise diagnosis, which would lower the malpractice pressure on physicians. Hence, both of these explanations hardly explain the absence of an effect.

One of the most likely explanations for the absence of an effect of tort reforms on the length of office visits is that physicians are constrained in their time allocation. Two constraints that come to mind are ethical and financial constraints. With regard to the former, it is clear that physicians in U.S. ambulatory care are generally short on time when treating patients (Linzer *et al.* 2000) and may, as a matter of fact, already be at the lower bound of what they think is ethically acceptable care. On the other hand, physicians are pressed to earn money, and spending more time with patients generally does not increase a physician's revenues, as opposed to ordering more tests and procedures. This may explain why physicians do not want to increase the time per visit. If both of these constraints are binding, physicians are effectively unable to adjust the length of office visits, be it in response to tort reforms or any other changes.

3.7 Conclusion

What is the impact of tort reforms on the practice of medicine? Much of the literature on tort reforms has focused on their impact on the use of procedures and treatments, such as Caesarean sections, coronary artery bypass grafting, imaging services, and prescription drugs. While the conclusions vary on a case-by-case basis, many papers have found that tort reforms influence physicians' decisions. In contrast to these findings, I show in this paper that tort reforms, with the possible exception of reforms of the collateral-source rule, do not affect how much time physicians spend with patients. Among the most likely explanations for this finding are ethical and financial constraints that deter physicians from adjusting the length of office visits.

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