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DISCUSSION PAPER SERIES

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ABSTRACT

Subjective Expectations for Health Service Use and Consequences for Health Insurance Behavior*

I evaluate the accuracy of people's subjective probability expectations for using various health services. Subjective expectations closely reflect patterns of observed utilization, are predicted by the same covariates as observed utilization, and correlate with objective measures of risk. At the same time, observable characteristics like age and health are weakly predictive of service demand. Through a series of examples, I demonstrate how subjective expectations can provide new insights about health behavior, specifically in the areas of asymmetric information, moral hazard and estimating welfare attributable to private care. The findings support collecting subjective expectations about health services in household surveys for use in applied research.

JEL Classification: D82, D84, I11, I12, I13

Keywords: subjective expectations, beliefs, subjective probabilities, health insurance, healthcare demand

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1 Introduction

Modelling demand for health services is challenging since observable risk factors often provide limited information on individual risk. Observable risk factors also tell us nothing about people's risk perceptions. If beliefs are biased, then correlations between objective risk factors and behaviors, such as insurance purchase, may be weaker than expected due to omitted variable bias, leading to incorrect inferences about people's behavior.

In many fields, researchers have used subjective probability expectations as a way of dealing with the unobservability of beliefs. Examples include job insecurity (Manski & Straub, 2000), future income (Dominitz & Manski, 1997; Delavande & Zafar, 2019), long term care (Finkelstein & McGarry, 2006) and investment markets (Hudomiet et al., 2011; Hurd et al., 2011). Studies in the health domain have generally focussed on subjective expectations for specific diseases, adverse health and mortality. They have tackled diverse questions, for example, how beliefs about HIV risk are shaped by information (Delavande & Kohler, 2012) and affect sexual behavior (Delavande & Kohler, 2016), how people self-select into annuity insurance (Finkelstein & Poterba, 2004), how expectations about risks from smoking (Viscusi, 1991; Lundborg & Lindgren, 2004; Khwaja et al., 2009) and alcohol consumption (Lundborg & Lindgren, 2002; Sloan et al., 2013) inform behavior and how expectations towards afflictions like influenza, breast cancer and heart disease affect preventative care use (Carmen & Kooreman, 2014). These studies demonstrate the wide-ranging application of subjective expectations to health behaviors research.

In this paper I focus on subjective expectations for health service use, rather than expectations for particular health outcomes. This distinction is important; in many situations, final demand for health services is of primary interest, rather than the foundations of that demand. For example, policy makers and insurers are interested in people's expected probability of hospital admission, in part because this is expected to be the most fundamental driver of demand for private insurance. This is particularly true in mixed public/private healthcare systems where consumers are protected from the intensive margin because they either face only the cost of the deductible when they receive private treatment, or can access free public care. Eliciting a single probability over the likelihood of hospital admission is also likely to generate more accurate information than eliciting a high dimensional vector of probabilities over all the possible diseases and risk factors that could potentially lead to a hospital admission (and is certainly more feasible). It therefore offers a practical way forward when coarsely defined service use is the variable of interest.

The primary goal of this paper is to assess the accuracy of subjective expectations over health service use, specifically hospitalizations and visits to ancillary care providers (dentists, optometrists, physiotherapists and related care providers, naturopaths and massage therapists). While subjective expectations have proved to be reliable predictors of objective risk and behavior in a number of settings (see Manski, 2004; Hurd, 2009, for reviews), they have not yet been assessed for health services.[1] Further, there is reason to question how much these measures reflect actual probabilities in the health care domain. In a classic study on biased beliefs, Lichtenstein et al. (1978) provide evidence of systematic bias in judgements of risk of death from various illnesses and events. Overall, people tend to overweight (underweight) low (high) probability events. Weinstein (1982) and Weinstein (1987) show that people are systematically overconfident with respect to their risk of developing health problems (see also Arni et al., 2020). At the same time, people overestimate their risk of death from influenza, developing breast and lung cancer and suffering from heart disease and stroke when compared to objective predictions (Khwaja et al., 2009; Carmen & Kooreman, 2014). People also over-predict risks associated with smoking (Viscusi, 1991; Lundborg & Lindgren, 2004) and alcohol (Lundborg & Lindgren, 2002; Sloan et al., 2013). These findings suggest that people may have biased perceptions about health service use.

On the other hand, it may be easier for people to form unbiased expectations about

[1] Although not strictly health service use, Finkelstein and McGarry (2006) provide evidence that subjective expectations for long-term care use convey meaningful information about risk that is independent of objective risk scores. Bruine de Bruin et al. (2011) asked people about their expected probability of getting a swine flu vaccination. They did not assess the accuracy of this expectation but did show that it positively correlated with perceived risk of contracting swine flu.

health service use than disease risk. People will often have personal experience with health service providers to draw on. They can think about how frequently they, or their friends and family, have been hospitalized in the past. Some service use will also be planned in advance. Finally, frequencies for these events are generally much higher than the risk of any particular ailment, which may suppress the tendency for people to overweight low probability events.

I elicit subjective expectations in a large online survey where people are asked to state their likelihood (0-100%) of utilizing various types of health services. I assess the accuracy of people's responses in a number of ways. I am able to show that these measures are positively correlated with objectively predicted risk, that they closely match the actual rates of health service use, and that the partial correlations between covariates like age and gender and expected vs. realised outcomes are similar. Bias in perceptions is generally in the direction of underestimating future health service use.

A second goal of this paper is to demonstrate how subjective expectations for health services can be used in research, with applications to topics in health insurance. Results are in the context of the Australian health insurance market, where private health insurance (PHI) operates parallel to universal public cover. This setting is interesting because one type of insurance (hospital cover) is duplicate to public insurance, while another type (ancillaries cover) is supplementary – risk may well play a different role in these settings. I first test for asymmetric information using the correlation between risk and insurance (Chiapori & Salanie, 2000). Consistent with previous research, I find no evidence of adverse selection in the case of hospital cover (e.g. Doiron et al., 2008; Buchmueller et al., 2013). Expanding on previous research I am able to show that the overall zero correlation masks interesting non-linearity in the risk/insurance relationship. This is valuable because it can be used to understand the decision function (for example whether probability weighting is being applied).

I then turn to ancillaries cover. There is a strong positive correlation between subjective risk and insurance for these services (i.e. dental, optical, physiotherapy, naturopathy, massage), which implies either large adverse selection or moral hazard effects. Using an instrumental variables approach, I provide evidence that the effects are largely attributable to moral hazard. Much of this effect is due to insurance increasing the probability of certain (i.e. 100% probability) utilization, which I argue implies that *ex ante* rather than *ex post* moral hazard is dominant.

Finally, I estimate a simple structural model of demand for private hospital insurance to demonstrate the potential of subjective expectations data for estimating welfare effects associated with the quality gap between private and public hospital care. The lack of positive correlation between risk and insurance suggests the inappropriateness of a standard expectations model. Allowing for heterogeneous preferences improves model fit.

This research points to the value in collecting subjective expectations about future health service use. Questions on expectations could be included in large household surveys at minimal cost. They would be particularly valuable in longitudinal surveys where expectations can be compared to outcomes. Longitudinal data would also allow for more credible estimation of structural models, which take into account dynamics in demand for services and insurance. The results also suggest value in leveraging people's private information about subjective risk, for example in health insurance plan selection software.

The paper is organized as follows. Section 2 describes the data, Section 3 assesses the accuracy of subjective expectations, Section 4 demonstrates the use of expectations data in health insurance research and Section 5 concludes.

2 Data

2.1 Datasets

This study uses two survey datasets. The primary dataset (Online Survey) is a sample of 1,528 Australians aged 25-64 years who were surveyed between 10-21 December 2015. These people were recruited by the market research company Qualtrics from their online research panel. The main component of the survey was a discrete choice experiment related to insurance choice, which has been analysed elsewhere (see Kettlewell, 2020). In addition to this experiment, respondents were asked a number of questions about demographics, risk preferences and subjective expectations regarding health service use. Quotas for age, sex and education were used to improve representativeness of the sample. Table 1 compares the Online Survey sample to population benchmarks and shows that this sample is observationally similar to the general Australian population of 25-64 year olds on many dimensions, although does have lower income and employment.

Table 1: Descriptive statistics (mean values)

	Sample	Population
Age 25-34	0.228	0.272
Age 35-44	0.234	0.254
Age 45-54	0.227	0.251
Age 55-64	0.311	0.223
Male	0.492	0.491
University	0.265	0.283
Couple	0.619	0.613
Employed	0.616	0.703
PHI (hospital)	0.491	0.497
PHI (ancillaries)	0.501	0.548
Household income		
<$60K	0.435	0.239
$60K–<$125K	0.392	0.373
$125K+	0.173	0.388

Note: Sample size is 1,528. Couple refers to those in either registered marriages or de-facto relationships. University indicates highest qualification is bachelors degree or higher. Population values for age, sex, university, couple and employed are from the 2016 Australian Bureau of Statistics (ABS) Census. APRA figures (June 2016) and the 2016 ABS Census have been used for PHI coverage. Population figures for income are weighted values from the 2015 wave of HILDA.

The second dataset is the Household, Income and Labour Dynamics in Australia Survey (HILDA). HILDA is a nationally representative household panel that has been tracking Australian households since 2001. It began with a sample of 19,914 individuals belonging to 7,682 households. In 2011 the sample was topped-up with an additional 2,153 households. I use data from the 2013 wave of HILDA, which is the most temporally close wave to the

Online Survey (2015) in which information on private health insurance and health service use is available (excluding waves after 2015). Data from HILDA are used to build prediction models for health service use which are then applied to the Online Survey sample in order to assess the accuracy of subjective expectations. There are around 9,000 individuals used in the prediction models (with sample sizes varying slightly by outcome variable) after restricting the HILDA sample to those aged 25-64 years with no missing information on the covariates common to both surveys.

2.2 Institutional background

Before discussing the main variables, a brief discussion about health care in Australia is necessary. All Australians have access to free public insurance for hospitalization through a scheme known as Medicare, which covers admissions to public hospitals. People can also purchase private hospital insurance to cover fees at private hospitals (or as a private patient in a public hospital), often with co-payments. Public hospitals are a high quality alternative to private care in Australia; the main advantages of going private are reduced waiting periods for elective surgery, the ability to choose your physician and potentially more pleasant care (e.g. use of a private room). Ancillary health services are out-of-hospital services not included in Medicare and are generally private fees.[2] Private ancillaries (or 'general treatment') health insurance can be purchased to cover these expenses. The structure of these policies varies, but generally they provide capped coverage for costs associated with dental, replacement corrective eye-wear (diagnostic visits to an optometrist are usually covered by Medicare) and physiotherapy and related treatments. Some more expensive policies also cover naturopathy and remedial massage. As of December 2019, 44% of Australians have some form of private hospital insurance and 53% private ancillaries. The majority of policies are combined hospital/ancillaries policies (83%).[3]

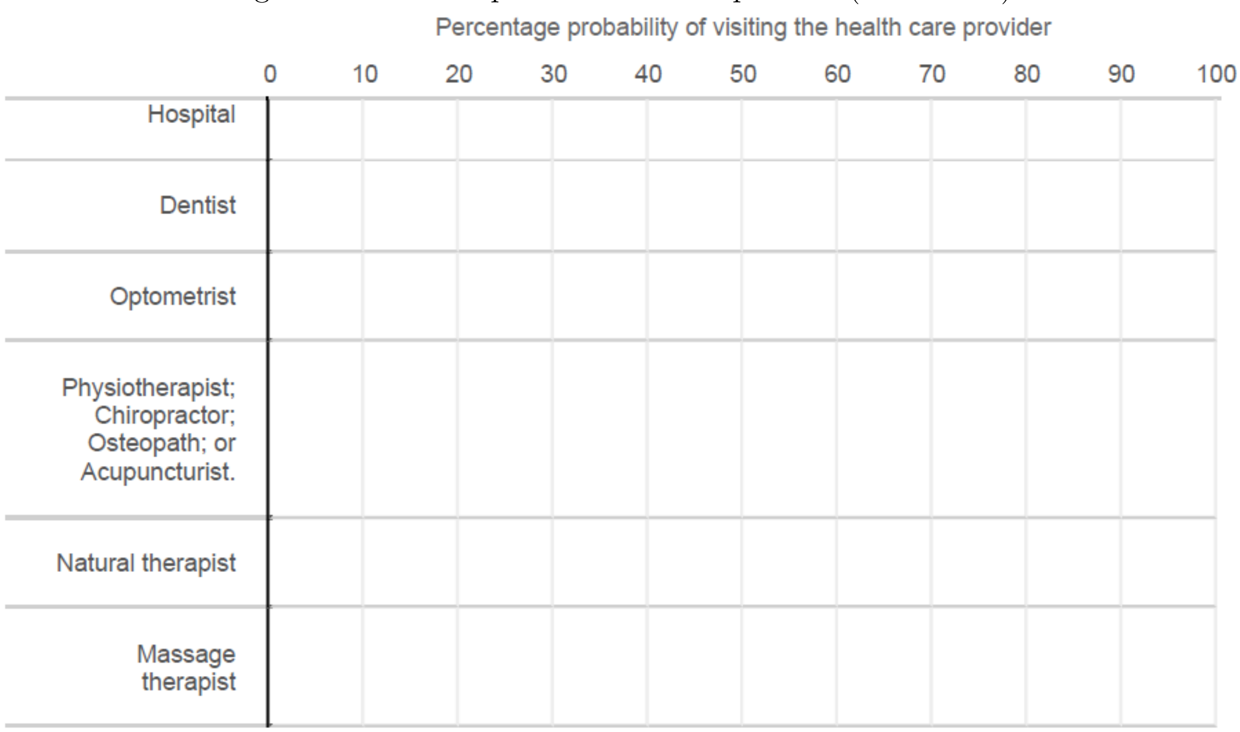
[2] It is possible to get some reimbursements through allied health care plans, which allow partial Medicare assistance for a limited number of visits to ancillary health service providers at the direction of a general practitioner.

[3] Industry statistics are available at `https://www.apra.gov.au/industries/private-health-insurance`

2.3 Main variables

The key variables for this study are people's expectations about health service use. Participants in the Online Survey were asked: "*For each health service below, use the slider to indicate how likely (from 0% to 100%) you are to visit this type of health care provider in the next 12 months*" (see Figure 1). Slider tasks have been shown to reduce the tendency for responses to bunch at 50% compared to open responses (Bruine de Bruin et al., 2002). The health services were chosen to match the services that are typically covered by private hospital insurance (hospital admissions) and private ancillaries insurance (dental, optical, physiotherapy (and related), naturopathy and massage). Respondents were only asked about the extensive margin of health service use in part because this matches the information that is collected in HILDA and can therefore be validated.[4]

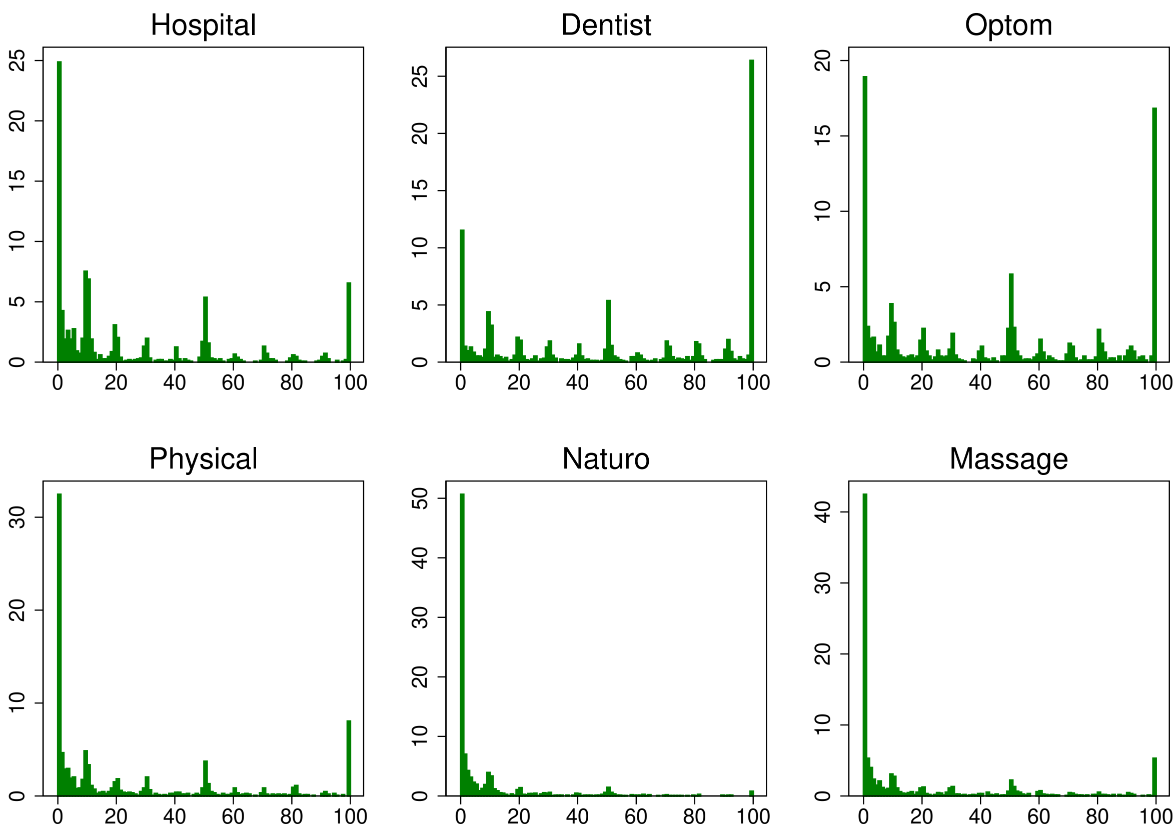
Figure 1: Stated expectations slider question (screenshot)



[4]These binary measures are also available in other major Australian health surveys e.g. the National Health Survey, the Australian Longitudinal Survey of Women's Health and 45 and Up. There may be additional value in eliciting expectations around the intensive margin, as well as expected expenses and their distribution; this is left for future work.

The distributions for the health service expectations (Figure 2) reflect some common features of these measures, namely bunching at 0%, 50% and 100%, and a tendency for people to round to 5s and 10s (Manski, 2004).[5] The bunching at 0% and 100% is particularly evident. It is not surprising that many people are certain about visiting a hospital (6.02%), dentist (24.48%), optometrist (15.58%) and physiotherapist (7.33%) since hospital admissions for elective procedures are known in advance, while it is common for people to have regular scheduled visits to ancillary service providers.

Figure 2: Distribution plots for subjective expectations



Note: Distribution plots show the percentage frequencies in the Online Survey for each subjective expectation of visiting the relevant health service provider in the next 12 months. Participants could respond in units of one percentage point. n=1,528.

[5]I do not address measurement error due to rounding in this study. In principle, it may be possible to learn something about bunching by exploiting the fact that there are multiple stated probability questions. The intuition is that we can learn about a person's tendency to round by observing their repeated choices (see e.g. Manski & Molinari, 2010).

The other key variables are self-reports for whether the person used the relevant health service provider in the last 12 months. These are matched to the stated expectation questions with minor exceptions (see Appendix Table A2). The main exceptions are: i) in the Online Survey people are asked about visits to a physiotherapist, chiropractor, osteopath or acupuncturist, while in HILDA they are asked about the first three only; ii) in HILDA, we observe visits to a 'naturopath, herbalist or acupuncturist' while in the Online Survey we only observe visits to a naturopath and; iii) we do not observe massage therapy for the HILDA sample. Acupuncture comprises a trivial fraction of the variable 'Physical' in the Online Survey, so (i) is of minimal concern.[6] Because of (ii) and (iii) I do not consider Naturo and Massage when comparing subjective expectations to objective predictions based on HILDA.

Other key variables are the observable characteristics that are common to the Online Survey and HILDA, which are used to build the prediction models. These include characteristics that are likely to reflect preferences, risk and financial means e.g. age, education, sex, employment status, insurance status, risk preferences, household composition, self-assessed health and regional indicators (see Appendix Table A1 for a complete list of variables and definitions). Previous work has established that many of these controls predict hospitalizations (see e.g. Buchmueller et al., 2013; Doiron & Kettlewell, 2018) and ancillary health service utilization (Kettlewell, 2019b), particularly age, gender, income, health and insurance.

One aspect of language in the Online Survey is worth commenting on. When asking people about prior health service use they are asked "*Did you visit any of these health care providers in the last 12 months?*" [Categories: hospital, dentist, optometrist, physiotherapist, chiropractor, osteopath, acupuncturist, naturopath, massage therapist].[7] This language matches how the question about subjective expectations was asked; however, it is possible for both questions that some people included visits on behalf of another person (for example

[6] Only five people in the Online Survey visited an acupuncturist in the last 12 months and did not also visit a physiotherapist, chiropractor or osteopath.

[7] They were also asked about how many visits they had. However, subjective expectations were only elicited for the probability of any visit, so I do not use this information.

their child or spouse). If so, it might be more accurate to think of health service use in this study as *contact* with particular service providers (which may or may not involve personal care). In Appendix B I explore this further and show that for most categories, reported health service use is indeed slightly higher in the Online Survey than in HILDA even after adjusting for covariates. In all cases except Optom this gap disappears when restricting attention to singles without dependent children, suggesting that for this group prior service use reflects personal care only.[8] For this reason I conduct analysis on the accuracy of subjective exceptions on i) the whole sample and ii) separately on singles without dependent children.

3 Accuracy of subjective expectations

Ideally, we would compare people's subjective expectations to their actual health service use in the future. Since the Online Survey is cross-sectional, this is not possible. Instead I use three common approaches to assess the accuracy of people's beliefs. First, I compare the aggregate predicted health service use in the next 12 months to the aggregate actual health service use during the last 12 months. Second, I compare the coefficients from models that estimate the past health service use and subjective expectations. Third, I use the HILDA sample to build a prediction model for expected probability of health service use and use this prediction as an objective measure of risk. The correlations between objective risk and subjective expectations are then compared.

3.1 Mean expectations

In Table 2 I compare the mean probability of having used each health service in the last 12 months to the mean subjective probability of using the service in the next 12 months. Assuming negligible ageing and time effects, we should expect these values to be similar if people's expectations are well-formed. Differences in the means will provide information on

[8]The persistent gap for optometry may be due to more restrictive wording in HILDA, as discussed in Appendix B.

the direction and magnitude of any bias in people's beliefs.

Table 2: Mean realized probabilities vs. expected

	Past	Expected	Diff	P-value
		A. All sample (n=1,528)		
Hospital	0.317	0.243	0.074	0.000
Dentist	0.573	0.527	0.046	0.004
Optom	0.477	0.425	0.052	0.001
Physical	0.270	0.241	0.029	0.042
Naturo	0.048	0.089	-0.041	0.000
Massage	0.176	0.186	-0.010	0.411
		B. Childless singles only (n=482)		
Hospital	0.255	0.190	0.065	0.005
Dentist	0.527	0.496	0.031	0.288
Optom	0.384	0.384	-0.000	0.996
Physical	0.226	0.218	0.008	0.739
Naturo	0.039	0.075	-0.035	0.002
Massage	0.139	0.162	-0.023	0.259

Note: 'Past' is an indicator for if the person reported visiting the relevant health service provider in the last 12 months. 'Expected' is the expected probability of health service use in the next 12 months. P-values are based on standard paired t-tests.

Looking at Panel A (full sample), overall the expectations are similar to the past probabilities, although the differences are statistically significant in all but one case (Massage). For the main health services (Hospital, Dentist, Optom, Physical) people tend to underestimate their probability. The degree ranges from 9% (Dentist) to 30% (Hospital). The higher discrepancy for Naturo (-46%) could reflect its low frequency. As discussed in the previous section, it is worthwhile separately looking at childless singles, whose responses are less likely to be confounded with health service use by others. For this group, expectations are closer to realizations – only differences for Hospital and Naturo are significant.

One unique challenge in interpreting expectations around health services is that these may be influenced by moral hazard. For the insured, expectations are likely to be underpinned by both personal risk as well as anticipated induced usage due to lower price of access. Differences in expectations bias between the insured/uninsured could matter for market outcomes. It is therefore worthwhile considering these groups separately, which I do in

Table 3.[9]

Table 3: Mean realized probabilities vs. expected

	Past	Expected	Diff	P-value
	A. All privately insured (n=751 [766])			
Hospital	0.314	0.239	0.076	0.000
Dentist	0.727	0.676	0.051	0.014
Optom	0.594	0.524	0.070	0.002
Physical	0.359	0.332	0.027	0.215
Naturo	0.060	0.114	-0.054	0.000
Massage	0.234	0.242	-0.008	0.677
	B. All not privately insured (n=777 [762])			
Hospital	0.320	0.248	0.073	0.000
Dentist	0.419	0.377	0.042	0.060
Optom	0.360	0.326	0.033	0.122
Physical	0.180	0.149	0.030	0.070
Naturo	0.035	0.063	-0.028	0.001
Massage	0.118	0.130	-0.012	0.407
	C. Privately insured childless singles (n=194 [201])			
Hospital	0.294	0.190	0.104	0.006
Dentist	0.701	0.682	0.019	0.643
Optom	0.527	0.496	0.031	0.481
Physical	0.348	0.331	0.018	0.679
Naturo	0.055	0.099	-0.044	0.037
Massage	0.199	0.223	-0.024	0.506
	D. Not privately insured childless singles (n=288 [281])			
Hospital	0.229	0.190	0.039	0.190
Dentist	0.402	0.363	0.039	0.282
Optom	0.281	0.304	-0.023	0.505
Physical	0.139	0.138	0.001	0.965
Naturo	0.028	0.057	-0.029	0.024
Massage	0.096	0.118	-0.022	0.328

Note: See Table 2. Private health insurance means hospital insurance for n not in square brackets, and any form of ancillaries insurance for n in square brackets.

While the insured tend to utilize ancillary health services more often than the uninsured,

[9]Expectations may also differ because the insured anticipate shorter waiting periods for hospital care. However, longer waiting periods for public care will also mean that the uninsured should have higher residual expectations for hospital care not yet received from health shocks in previous periods. On net, these effects should cancel out. It may be worthwhile in future work to include an additional subjective expectations question about only expected hospitalizations due to future events, and to jointly elicit expected waiting periods.

there are no strong differences in the gaps between past and expected use by insurance status when focussing on the full sample (Panels A and B). Both groups underestimate their use of the main health services by a similar degree. This is also the case when looking at childless singles (Panels C and D) with one important exception. The underestimation of hospital usage is -35% for the insured compared to -17% (statistically insignificant) for the uninsured. This indicates that the gap may be partly explained by unanticipated *ex post* moral hazard. The fact that we only see this difference for hospitilizations can potentially be explained by the fact that hospitalizations are often due to unexpected health shocks, whereas visits to dentists, optometrists etc. are more likely to be expected.

3.2 Comparing coefficients: Subjective expectations vs. realized usage

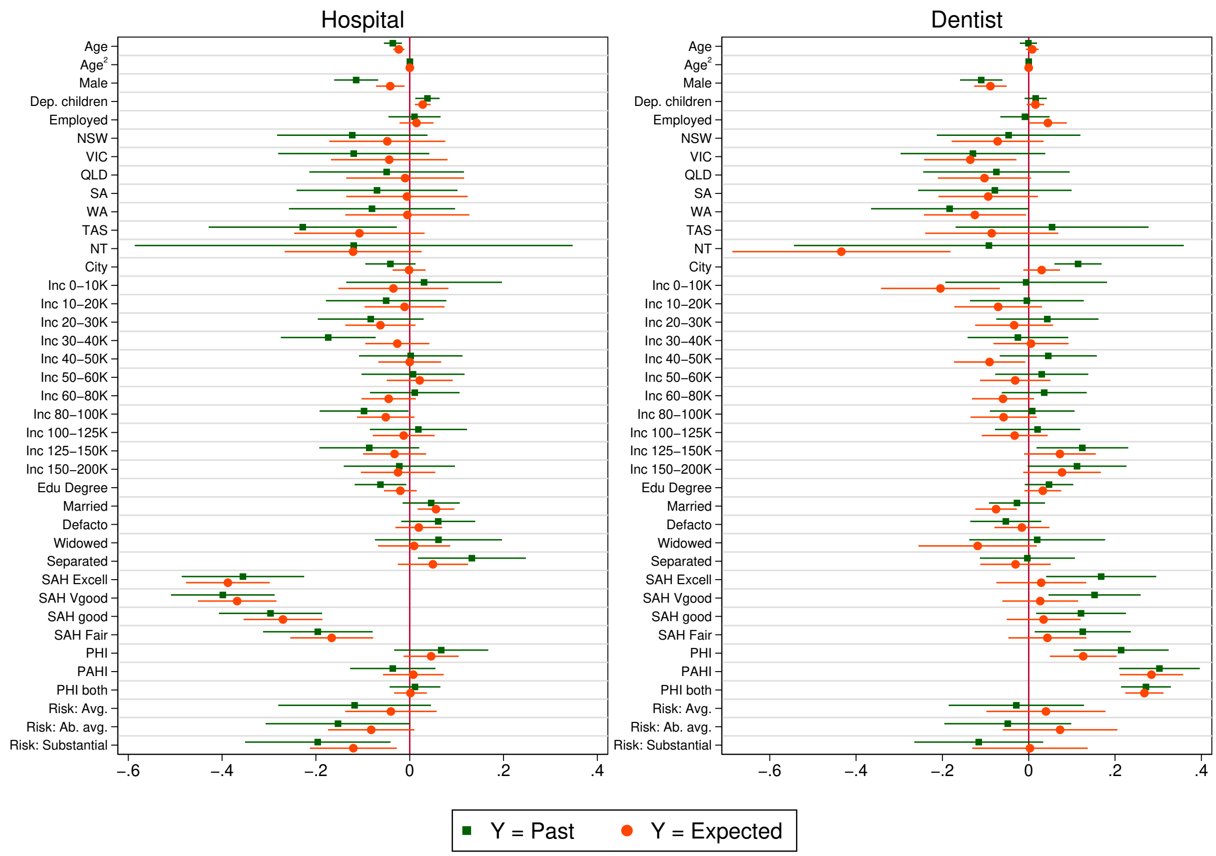
In this section I compare partial correlations between covariates and past risk and covariates and expectations. If people's expectations are accurate, then these correlations should be equal. Similarity between the partial correlations would also be consistent with people updating (potentially biased) beliefs like Bayesians in response to knowledge about their risk factors (e.g. health).

Figures 3-5 compare coefficients from linear regression models using the full sample. For each health service, the comparison is between the estimates from a linear probability model on the past realization (e.g. hospital admission) estimated by OLS, and a linear regression on the subjective expectation. The coefficients are also reported in the Online Appendix Tables A3 and A4. For the sake of space, figures for childless singles are relegated to the Appendix (Figures A1–A3).

Figure 3 considers Hospital and Dentist. Although tests on the joint equality of the entire vector of coefficients reject equality,[10] the coefficients almost always have the same sign, and

[10]This was tested using Stata's *suest* command for a generalized Hausman test, with the intercepts excluded from the coefficient vector.

Figure 3: Coefficient estimates – Hospital and Dentist use

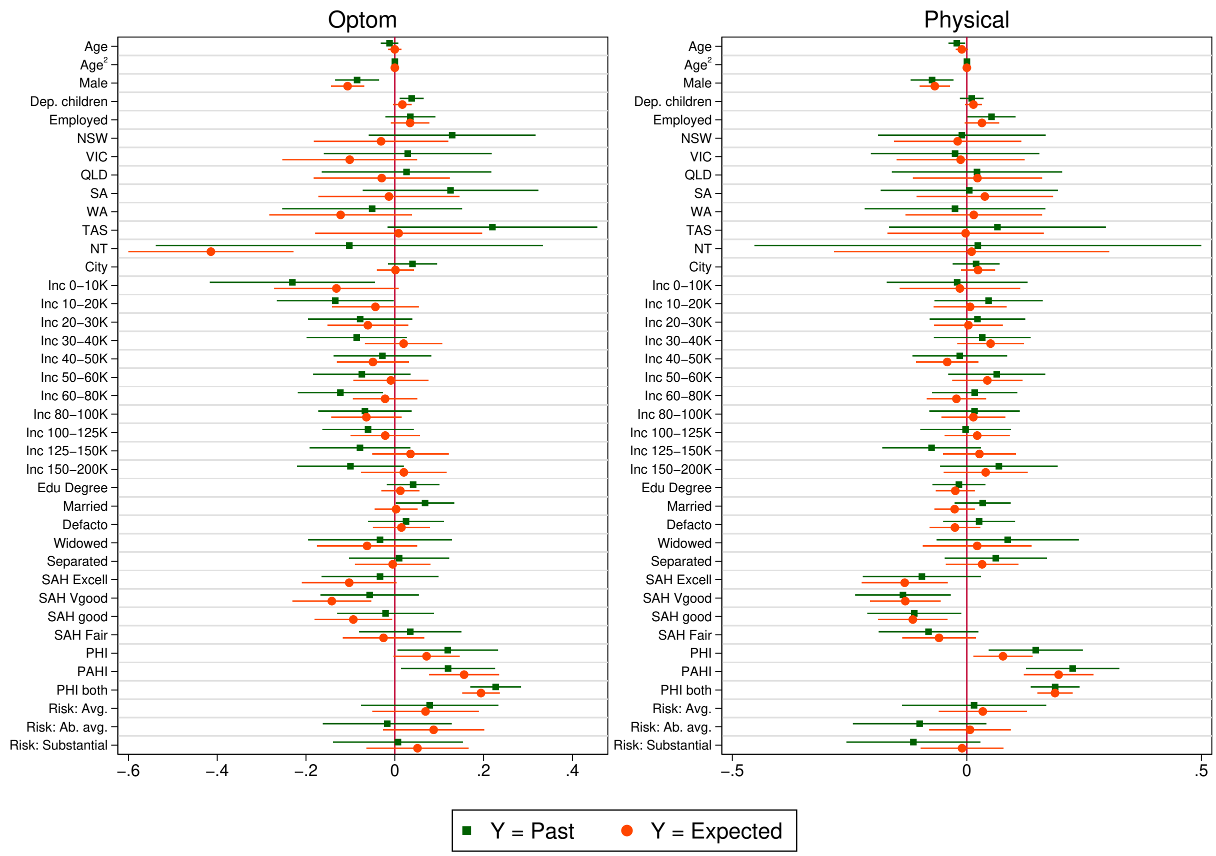


Note: Displayed are coefficient estimates and 95% confidence intervals (robust standard errors) from linear regression on an indicator for actual health service use in the last 12 months (squares) and expected probability of health service use in the next 12 months (circles). n=1,528.

when the signs differ usually one or both of the coefficients are statistically insignificant. Major correlates are consistent across models. For example, both past realizations and expectations are concave with respect to age and are significantly negatively signed with respect to being male, health and willingness to take risks. For dentist, correlations with expectations pick up the large partial effects from sex and insurance. Interestingly, the correlation for male is notably weaker for Hospital, which may suggest possible gender effects in the formation of expectations. However, across other health services there is no significant divergence on the male dummy.

Figure 4 looks at Optom and Physical. Again we see a general pattern of congruence between the estimates and both models suggest the same major predictors (i.e. age, sex,

Figure 4: Coefficient estimates – Optom and Physical use

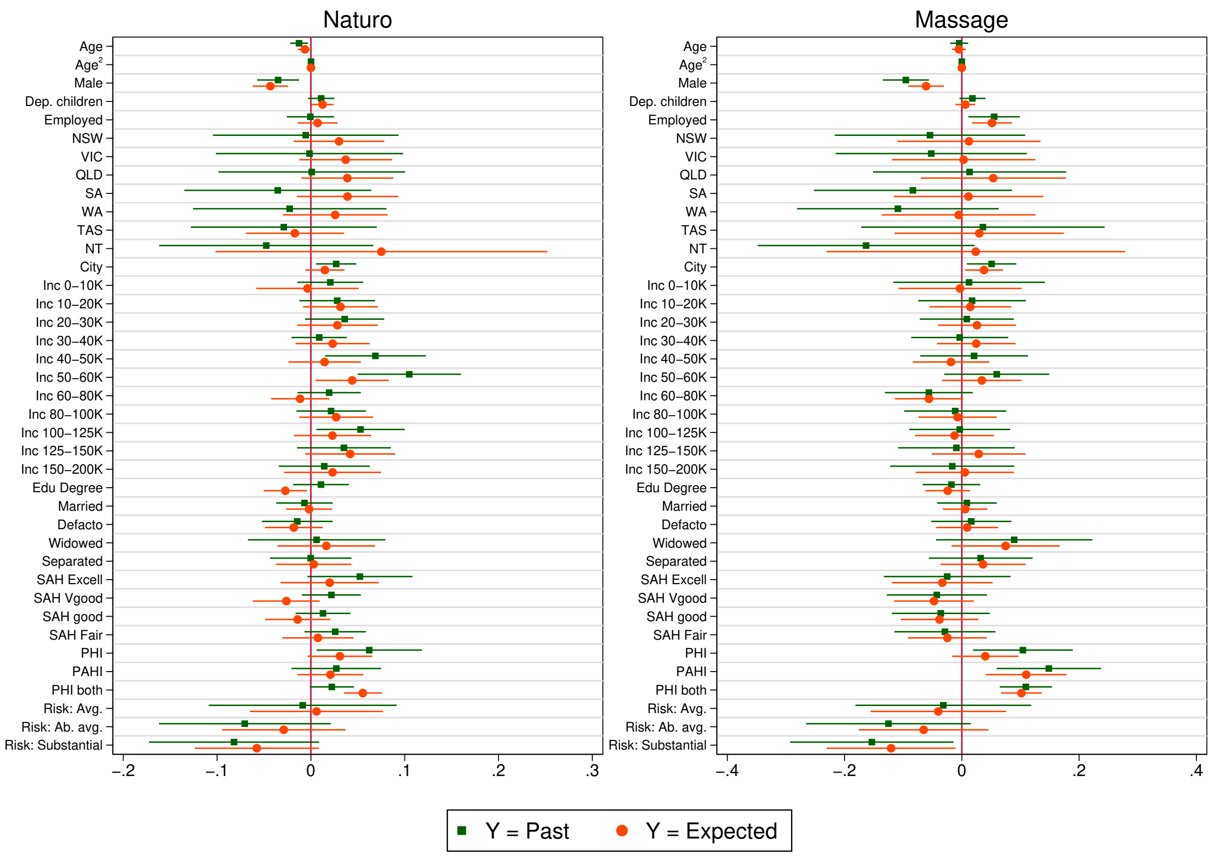


Note: See Figure 3

health, insurance). It is a similar story when we look at Naturo in Figure 5. In this case, age, sex and risk preferences are particularly influential in both models. Finally, the coefficients for Massage are strongly correlated; this is the only health service where we cannot reject joint equality of the coefficients ($p = 0.151$). The superior predictive validity for Massage is consistent with results in the previous section.

Results for childless singles are reported in Appendix Figures A1-A3 and Tables A5 and A6. These results are similar to those for the full sample, although some estimates are less precise, which is expected given the smaller sample. For this group, the joint equality of the coefficients cannot be rejected (at the 5% level) for Dentist, Optom or Physical.

Figure 5: Coefficient estimates – Naturo and Massage use



Note: See Figure 3

3.3 Correlations between expectations and objective risk

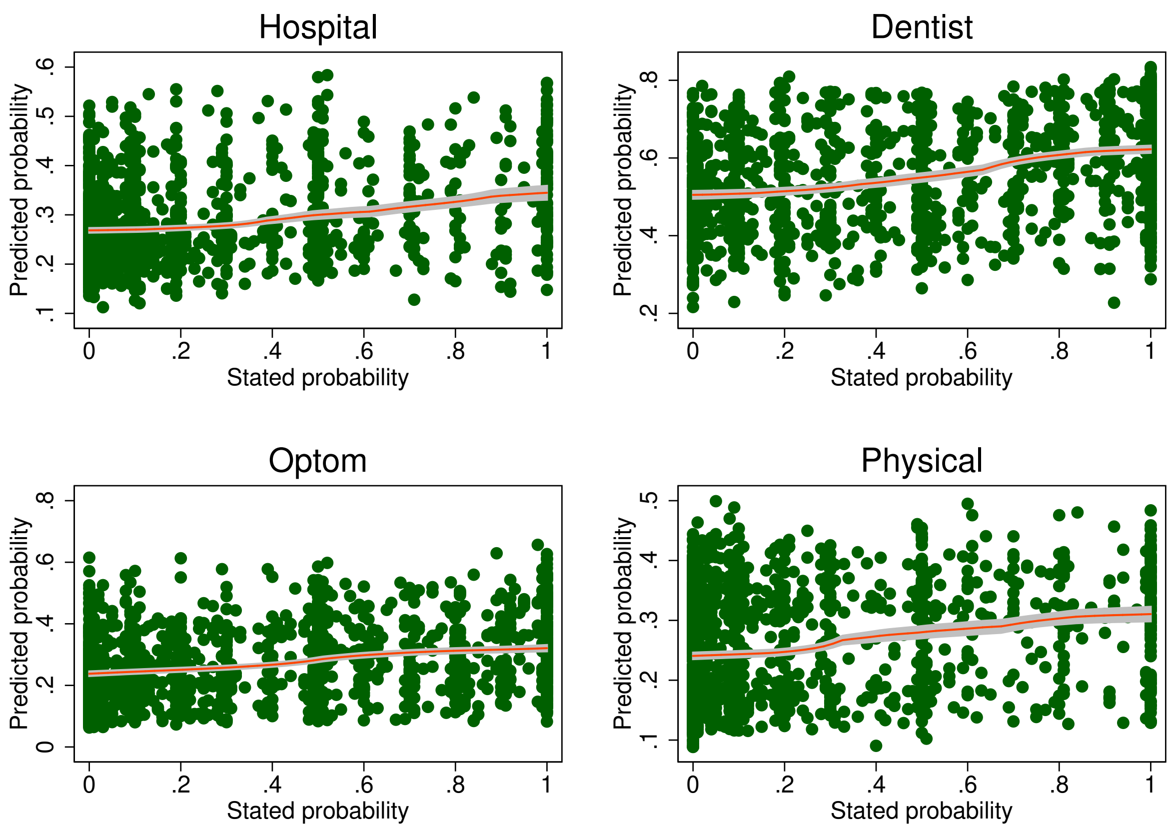
The final exercise on accuracy compares out-of-sample predictions to subjective expectations. Out-of-sample predictions are generated by estimating a logistic regression model using the HILDA sample to predict health service use in the Online Survey. The prediction model includes all the overlapping covariates in Table A1 and a full factorial of age dummies. These independent variables are all lagged by one year since expectations are for the next 12 months in the Online Survey. To improve predictive power, a penalized likelihood function is maximized using lasso logit regression (Ahrens et al., 2019), with the tuning parameter selected using K-fold cross validation and the preferred subset of covariates chosen based on a lowest deviance criterion.

One shortcoming of comparing out-of-sample predictions to expectations is that the correlation is likely to be low if the predictions are poor. On the other hand, difficulty obtaining accurate predictions from observable risk factors adds further weight to the importance of collecting information on subjective expectations. Indeed, despite a large set of covariates and rigorous estimation strategy, the models provide only low-moderate internal predictive power. The pseudo R^2 values range from 0.04 (Hospital) to 0.07 (Dentist) and the areas under the receiver operating characteristic (ROC) curves are between 0.62-0.68 (see Appendix Figure A4), slightly below the commonly accepted threshold of 0.7 for moderate predictive power.[11] In exploratory work I added an extensive set of additional health variables available in HILDA covering BMI, diet, exercise, smoking, drinking, social capital, various health conditions, ongoing treatments, mental health and sleep (72 variables in total). Even with this extensive set of controls, the range of pseudo R^2 and ROC values is 0.08-0.09 and 0.69-0.70 respectively, reflecting the difficulty in predicting health use from survey data, even with detailed health information.

Figure 6 reports scatter plots and local polynomial fits between the HILDA predictions and stated expectations for the full sample and Figure 7 reports the same correlations for childless singles only. In all cases the correlations are positive, with the following Pearson correlation coefficients for the full sample (childless singles): Hospital = 0.30 (0.32); Dentist = 0.39 (0.39); Optom = 0.33 (0.29); and Physical = 0.28 (0.32). While these correlations are not overly strong, they need to be evaluated against the low predictive power of the lasso logit models. Subjective expectations do seem to meaningfully correlate with an objective measure of risk.

[11] The ROC curves show how the fraction of correctly identified positive outcome cases (sensitivity) evolves as one minus the fraction of correctly identified negative outcome cases (specificity) increases. The area between the ROC curve and the 45 degree line (the ROC curve in a model with no predictive power) gives a measure of model fit ranging from 0 to 1, with higher values indicating better fit.

Figure 6: Correlations between subjective and predicted risk

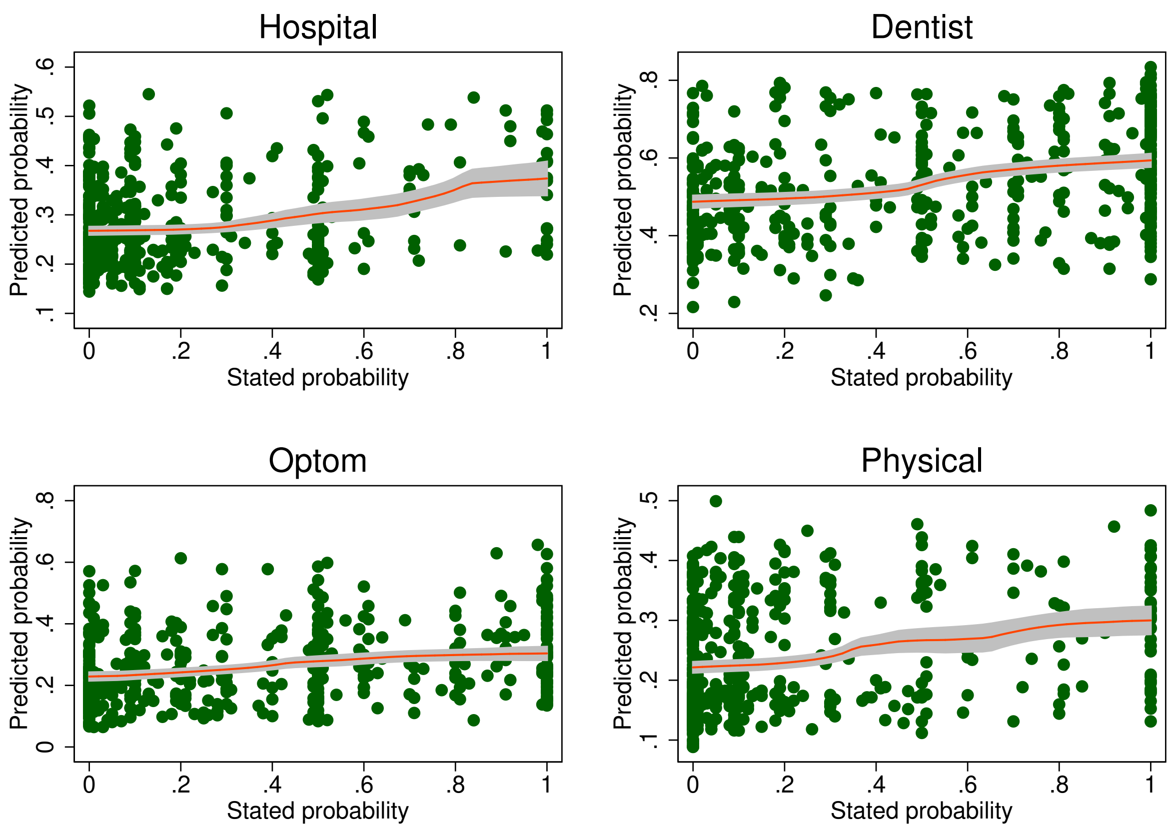


Note: Predicted probabilities are obtained by estimating lasso logit models on an indicator for actual health service use in the last 12 months using the HILDA sample and predicting health service use in the Online Sample from the resulting estimates. Stated expectations are the expected probability of health service use in the next 12 months. Data from the 2013 wave of HILDA are used for the prediction models. After restricting the sample to those aged 25-64 years with non-missing data, n=9,460, n=9,306, n=9,362 and n=9,460 for Hospital, Dentist, Optom and Physical respectively. n=1,528 in the Online Survey sample.

3.4 Summary

Subjective expectations closely reflect patterns of observed utilization, are predicted by the same covariates as observed utilization, and correlate with objective measures of risk. There is a moderate tendency towards underestimating risk on average for the highest use health services (Hospital, Dentist, Optom, Physical). This bias may be partly due to phrasing in the Online Survey leading to some reported health service use being on behalf of family members; for childless singles, the differences largely disappear. Childless singles without private health

Figure 7: Correlations between subjective and predicted risk for childless singles



Note: See Figure 6. n=482 childless singles in the Online Survey.

insurance also have more accurate beliefs about hospitilization risk than those with private health insurance, which could indicate the privately insured experience unanticipated moral hazard. Overall, the results support subjective expectations as a high-quality single control for health service risk.[12] The poor performance of observable risk factors in predicting utilization further supports the collection of subjective expectations data.

[12]While noting that the efficacy of subjective expectations is not necessarily tied to their ability to predict actual risk (consumers are assumed to act on expectations regardless of whether they are biased).

4 Applications

In this section I provide examples to demonstrate how subjective expectations data can be used to provide new insights, focussing on behavior around private health insurance. First, I study the correlation between risk and insurance, which is often used as a general test for asymmetric information. Second, I estimate the causal effect of insurance on subjective expectations. Third, I estimate a simple structural model of insurance choice and show how researchers could use subjective expectations to estimate welfare gains from private versus public treatment.

4.1 Asymmetric information in private health insurance

A standard prediction in insurance theory is a positive correlation between insurance and probability of claim. This can indicate that those selecting into insurance are an adverse selection of the general population. The correlation may also be due to moral hazard e.g. insurance increasing demand for health services by inducing people to take more risks and/or by lowering the effective cost of care. Chiapori and Salanie (2000) therefore suggest estimating the correlation between claim-risk and insurance (conditional on premium setting variables) as a general test for asymmetric information (which does not distinguish between these channels). Previous research has actually found a negative correlation between private hospital insurance and claim-risk (proxied by realized hospital admissions) in Australia, which Doiron et al. (2008) and Buchmueller et al. (2013) suggest may be partly due to heterogeneous risk preferences. In contrast, evidence on ancillary health services is consistent with the expected positive correlation between insurance and health care use (Kettlewell, 2019b).

Studying the correlation between subjective expectations and insurance can extend existing research by uncovering non-linearities in the claim probability/insurance relationship. It is also informative to test whether expectations correlate in the same way as realized usage since expectations can differ from actual utilization. In Figure 8 I fit a local polynomial line through a dummy for being privately insured against subjective expectations. Figure 9 repeats this exercise for childless singles only. Focussing on results for the full sample, the correlation for Hospital is highly non-linear and across the full range slightly negative. The non-linearity is informative; between probabilities 60-100% the correlation is strongly negative because the very high probability often select out of private insurance. There may be something unique about this group that increases their risk but lowers their probability of insurance. For example, gap fees associated with private cover could mean that those with very bad health are better off using the public system (or are forced to due to financial constraints). While this is difficult to explore with the current data, it would be possible to explore this by combining subjective expectations data with detailed health data. The relationship is flatter when the sample is restricted to childless singles only, so the result may also be an artefact of people responding to the subjective expectations question on behalf of others.[13]

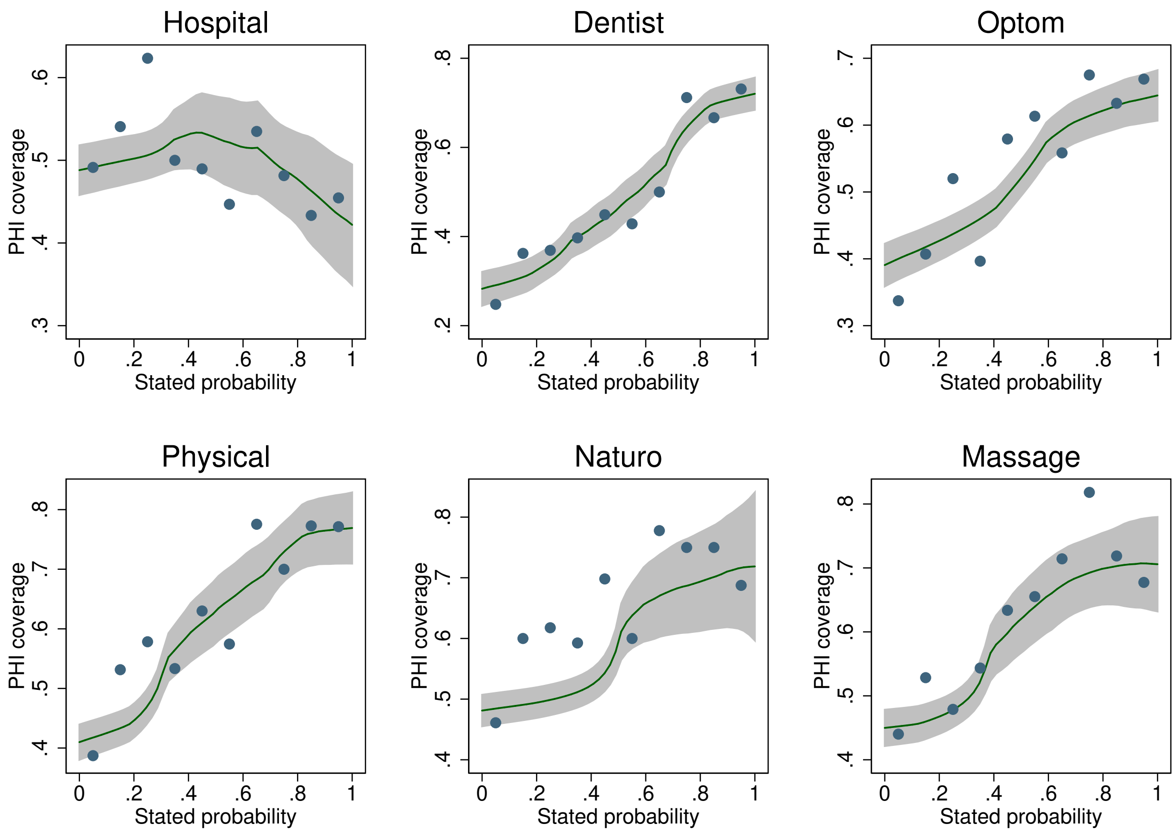
The correlations between the ancillary health services and private insurance are all strongly positive and approximately linear (with the exception of Naturo and Massage, which are non-standard items on private insurance policies).[14] These results are more consistent with classic adverse selection and/or moral hazard compared to the results for Hospital. There is no strong evidence of probability distortion in people's expectations. If, for example, people overweight (underweight) the importance of low (high) risk in their insurance decisions, then we would expect an S-shaped relationship between insurance and expectations (absent any omitted variable bias).

In Australia, demand for private health insurance is distorted by incentives created by

[13]People whose expectations include risk to others (e.g. family members) will have subjective expectations higher than their personal risk, which could help to explain a negative relationship. On the other hand, people typically purchase private health insurance as a family product, which suggests risk to family members should be positively correlated with own insurance demand.

[14]Although precise details on the services covered by each policy are not available, in practice most ancillaries policies include some cover for dental, optometry and some physical health services (e.g. physiotherapy, chiropractor).

Figure 8: Correlations between subjective expectations and private health insurance

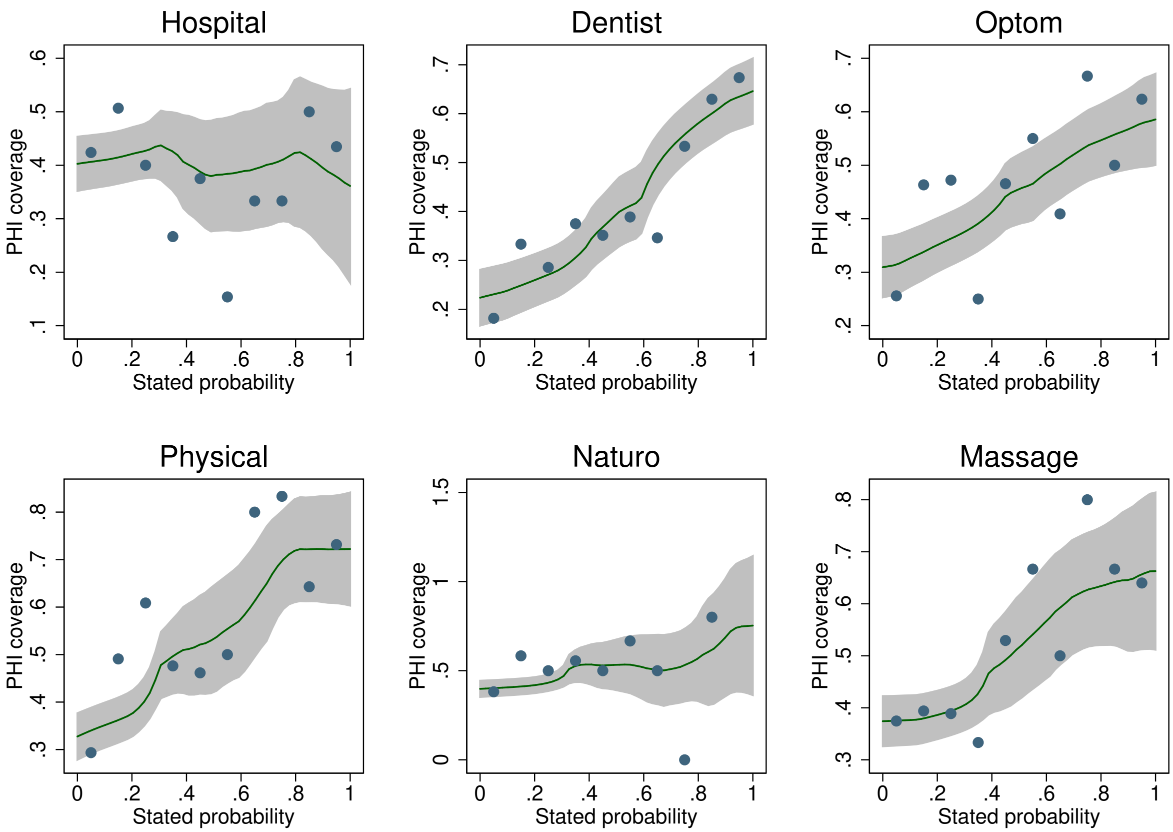


Note: For Hospital, private health insurance coverage is a dummy for any type of private health insurance policy that includes hospital cover. For other health services, coverage is any type of policy that includes ancillaries cover. Line fits and confidence intervals (shaded area) are based on local polynomial smoothing regressions estimated using Stata 14 (Epanechnikov kernel, 50 cut points and rule-of-thumb bandwidth). Scatter points are mean PHI coverage bins by deciles on stated probability. n=1,528.

income- and age-based penalties for those who do not privately insure (see Appendix C). Based on previous research, heterogeneous risk preference may also help to explain the profile for Hospital. In Appendix C I attempt to net out these policy and preference effects by flexibly controlling for income, age and risk preferences[15]; however, this does not significantly affect the relationships between subjective expectations and coverage (See Appendix Figures C2 and C3).

[15]Risk preferences are measured using i) stated willingness to take financial risks (four levels) and ii) hypothetical choices in an Eckel and Grossman (2002) lottery choice task (six levels).

Figure 9: Correlations between subjective expectations and private health insurance: Childless singles



Note: See Figure 8. There is one less scatter point for Naturo because nobody has a stated probability between 0.8-0.9. n=482.

4.2 Causal utilization effects

A challenge for health insurance research has been separating selection from moral hazard. Frequently, researchers have used instrumental variables to identify causal utilization effects. Hopkins et al. (2013) and Kettlewell (2019b) suggest using a person's need for corrective eyewear as an instrument for other ancillary health services like dental and physiotherapy. Relevance is due to the fact that most private ancillary health insurance policies cover replacement eyewear. People who wear glasses therefore have an increased incentive to insure. Validity rests on eyesight being strongly genetic (Williams et al., 2017) and, conditional on age, plausibly uncorrelated with visits to health service providers (other than optometrists).

I follow previous work and use an indicator for whether a person wears glasses as an instrumental variable and focus on Dentist and Physical as outcomes.[16] Again, I extend existing work by exploiting the distribution of risk. This allows me to estimate whether insurance affects both the probability of any utilization $\Pr(Y_i > 0)$ and the probability of certain future utilization $\Pr(Y_i = 100)$. Certain utilization is interesting to focus on because a strong effect on this margin would indicate that insurance is affecting *ex ante* behavior (i.e. future utilization plans). If insurance only affects *ex post* decisions (i.e. responding to the lower price of care after the adverse health event), then the overall subjective expectation when going from no insurance to insurance will equal Pr(adverse health event)$\times$Pr(receive medical care | adverse health event, PHI = 1), which is < 1 provided that Pr(adverse health event) < 1 (if Pr(adverse health event) $= 1$ then there is no moral hazard). It is typically difficult to distinguish between these margins of moral hazard without detailed health service records.

To derive an estimation model I assume that subjective expectations Y_i are not strictly bounded by [0,100]. Some people who respond with $Y_i = 100$ are actually more certain than others such that the latent subjective expectation is higher for these people. For those with $Y_i = 100$ we assume that their true $Y_i \geq 100$ (an analogous assumption is maintained for those at 0). The latent expected probability is then given by:

$$Y_i^* = \mathbf{X_i'B} + \beta_{PHI} PHI_i + \epsilon_i, \tag{1}$$

with $Y_i = 0$ if $Y_i^* \leq 0$, $Y_i = Y_i^*$ if $Y_i^* \in (0, 100)$ and $Y_i = 100$ if $Y_i^* \geq 100$. ϵ_i is assumed to be $N(0, \sigma^2)$ so that Eq. (1) can be estimated as a two-limit tobit. To estimate the causal effect of PHI on Y_i^* I use a control function approach where the generalized residuals from a probit regression of PHI_i on $\mathbf{X_i}$ and the instrumental variable (glasses) are included in (1) as an additional control. $\mathbf{X_i}$ includes the full set of controls described in Table A1.

[16] Given that naturopathy and massage are often not covered by ancillaries policies, I do not consider these as dependent variables. I also do not consider Hospital since private hospital insurance is a separate product to private ancillaries insurance (although in practice they are often sold as a bundle).

Consistent estimates for the average marginal effects (AMEs) are obtained by calculating the sample average changes in predicted probabilities when switching PHI from zero to one (Wooldridge, 2015). Estimation results are in Table 4.

Table 4: Regression results: Causal utilization effects

	Full sample (n=1,528)			
	Dentist		Physical	
β_{PHI}	37.94***	83.79***	27.49***	55.22***
	(3.24)	(21.42)	(2.80)	(19.42)
β_{RES}		-28.11**		-16.99
		(12.49)		(11.64)
AME $\Pr(Y \leq 0)$	-0.17***	-0.35***	-0.22***	-0.42***
	(0.01)	(0.08)	(0.02)	(0.11)
AME $\Pr(Y \geq 100)$	0.19***	0.43***	0.05***	0.10
	(0.02)	(0.09)	(0.01)	(0.05)
	Childless singles only (n=482)			
β_{PHI}	46.73***	69.36***	28.36***	51.86**
	(6.12)	(23.29)	(5.08)	(23.03)
β_{RES}		-14.32		-14.86
		(13.72)		(13.37)
AME $\Pr(Y \leq 0)$	-0.20***	-0.29***	-0.23***	-0.39***
	(0.02)	(0.08)	(0.04)	(0.13)
AME $\Pr(Y \geq 100)$	0.25***	0.37***	0.05***	0.10
	(0.04)	(0.12)	(0.01)	(0.07)

Note: Estimates are from two-limit tobit regressions and include the full set of controls as described in Table A1 (plus Age^2). Columns 3 and 5 include the generalized residuals from a probit regression on the instrument ("Do you currently wear glasses or contact lenses to correct, or partially correct, eyesight?") as an additional control. The instrument is highly relevant; the first-stage estimates imply that probability of insurance is 13.6% (SE = 0.03) higher for those who wear glasses in the full sample, and 22.5% (SE = 0.05) higher in the childless singles sample. Average marginal effects (AMEs) are the sample average change in the relevant probability when switching the insurance indicator from zero to one. Nonparametric bootstrap standard errors in parentheses (999 reps). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The baseline tobit estimates imply a positive correlation between insurance and stated expectations for both health services. After instrumenting, the effect of insurance is even larger. This may seem counter-intuitive given that adverse selection should bias the utilization effect upwards; however, recall that research on Australian private health insurance frequently finds evidence of favorable selection, which is consistent with the CF-tobit estimates being larger than regular tobit. The AMEs imply a 43 percentage points (ppts) increase in the probability of certain dental utilization due to insurance, and a 10 ppts increase in certain Physical utilization. There is also a large effect on the probability of any positive expectation (35 ppts and 42 ppts respectively). The results are robust to limiting the sample to childless singles only.

Combining this evidence with similar estimates from actual health service use (Kettlewell, 2019b), insurance seems to increase both utilization and *expected* utilization of ancillary health services. The large AMEs on $\Pr(Y_i) = 100$ (especially for Dental) are more consistent with *ex ante* moral hazard, which suggests more preventative care or treatment for pre-existing conditions. The social returns to preventive and reactive care are likely to be different, so this is useful information for policy makers.

4.3 Structural estimation

I now turn attention back to private hospital insurance and care.[17] Popular models of demand for private hospital insurance in the context of dual public/private healthcare systems assume that decision makers maximize utility subject to the price of insurance, their income and the quality gap between public and private care (Besley et al., 1999; Costa & García, 2003). This departs somewhat from classical insurance models because decisions are driven by preferences for quality health care rather than reductions in the variance of financial outcomes.

By estimating such models, researchers can make statements about the welfare associated with the quality gap between private and public care. Estimation is also important to test the consistency of these models with observed behavior. However, there have been few attempts at structural estimation. Typically researchers have modelled demand for private health insurance in dual system markets by assuming a linear index function (sometimes framed as an indirect utility function) that is weighted by observable characteristics like age

[17]Due to issues with convergence, I do not present separate estimates for childless singles in this section. These issues are likely related to limited variation in key variables like income, coupled with small sample size.

and gender, lending itself to probit and logit regression (see Kiil, 2012, for a review). Fully structural models have been estimated in settings where there is no universal safety net (e.g. Vera-Hernández, 2003; Bajari et al., 2014); however, the theory underpinning choice in that setting is not well-suited to dual market systems. A major challenge for structural estimation is that researchers do not observe the key variable in these models – expected hospitalization. It may be possible to estimate this, however results in Section 3 indicate that even with rich data, predictions may be quite noisy. Subjective expectations data can therefore offer an attractive alternative.[18]

In this section I estimate a basic structural model of demand for private hospital insurance based on Besley et al. (1999). This 'quality-gap' model is frequently drawn on to motivate reduced form analysis (e.g. Costa & García, 2003; Costa-Font & García-Villar, 2009; Johar et al., 2011). It relies on a state-based utility setup whereby people operate on a utility function with lower marginal utility of income when they are sick.[19]

It is important to point out that the purpose of this section is to simply demonstrate how subjective expectations *could* be used in structural work. As will become clear shortly, the simple model I estimate has several limitations that mean welfare estimates should not be relied on for policy setting. The Online Survey data are also severely limiting. However, many of these data limitations would be resolved if subjective expectations were included in household survey data (e.g. HILDA, the British Household Panel Survey etc.), where income is measured in a more detailed way and people are tracked over time.

4.3.1 Theoretical model

Denote $U^S(W; Q^i)$ as utility when sick and $U^H(W; Q^i)$ as utility when healthy. Q^i is the quality of care, with $Q^{PR} > Q^{PU}$ (private care is preferred to public). W is income (Y) net of the cost of insurance (π) for the insured ($W = Y$ for the uninsured). The following

[18] Manski (2004) argues more generally for the utility of subjective expectation in estimating economic choice models.

[19] See Finkelstein et al. (2013) for empirical support.

derivatives hold: $U^S_W, U^H_W, U^S_Q \geq 0$; $U^S_{WW}, U^H_{WW}, U^S_{QQ} < 0$ (utility is weakly concave in income and the quality of care); $U^S_{WQ} \geq 0$ (which ensures that quality care is a normal good); $U^H_W \geq U^S_W$ (the marginal utility of income is higher in the healthy state of the world).

In more advanced versions of the model, people can choose to privately fund private hospital care (Costa & García, 2003). Estimating this version would require knowledge of this private cost, which is difficult to obtain. In practice few people without insurance choose private care (Doiron & Kettlewell, 2018) and we ignore this possibility. Denoting the probability of hospitalization by η, people have the following value functions based on their expected utility.

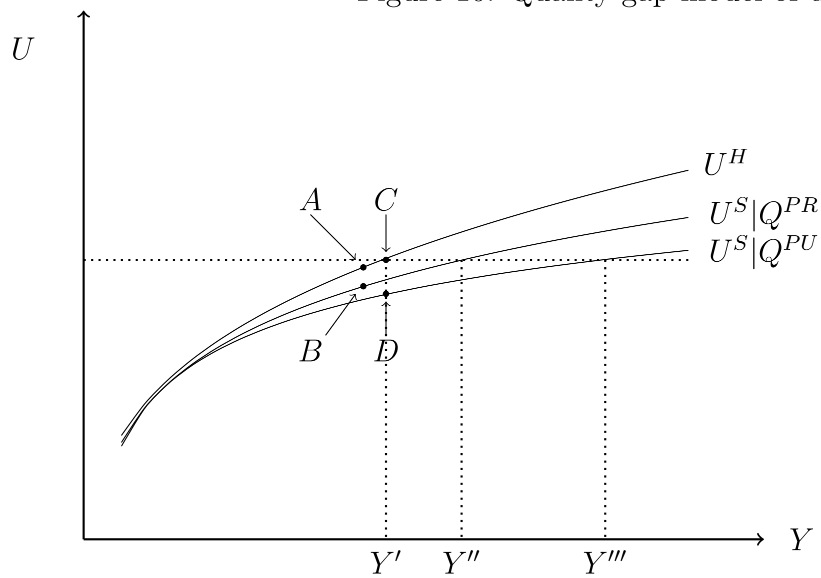
$$V_{phi} = \eta U^S(Q^{PR}; Y - \pi) + (1 - \eta)U^H(Y - \pi) \tag{2}$$

$$V_{pub} = \eta U^S(Q^{PU}; Y) + (1 - \eta)U^H(Y) \tag{3}$$

An individual will insure if $V_{phi} > V_{pub}$. To see how this model can be used to estimate welfare attributed to avoiding sickness and to the quality gap in care, it is helpful to present it graphically.

Figure 10 plots the utility curves under the three potential states of the world (healthy, sick with insurance, and sick without insurance) and the four possible outcomes represented in the value functions A, B, C, D. The horizontal distance between A and Y' reflects the cost of insurance π. The value function can in fact be written as $V_{phi} = \eta B + (1 - \eta)A$ and $V_{pub} = \eta D + (1 - \eta)C$. One thing that is clear in Figure 10 is that the utility cost of a health shock is larger for those on higher incomes. If we know π and observe income, insurance status and risk η then it is possible to estimate the separate utility functions. From there, welfare calculations are possible. For example, $Y'' - Y'$ represents the amount of monetary compensation required for a person receiving Q^{PR} care to be indifferent between the bad and good health state. The welfare associated with the quality gap can be measured by

Figure 10: Quality-gap model of utility



calculating $Y''' - Y''$ – this is how much compensation a person would need to be indifferent between private and public care.

While simple and intuitive, the model above has several limitations. For example, there is no role for dynamics, yet studies show that state dependence is an important driver of demand in Australia (Buchmueller et al., 2019; Doiron & Kettlewell, 2020). The model is also unclear about the planning period. In the present context, I assume people make decisions about the next 12 months, which may be reasonable since prices rise once per year (in April) and one-year is the usual contract length. Gap fees associated with private hospital care are ignored; however, these can be large.[20] Incorporating gap fees into the model would be challenging because they vary by contract and service. When gap fees are sufficiently large, people may choose not to use the private hospital system, even if they are insured, which is not incorporated in the current model. The model ignores the heterogeneity in health states and the intensity of sickness. For estimation, incorporating this kind of information would involve eliciting subjective expectations for e.g. the duration of hospitalization. The model

[20] In the September-December 2019 quarter, 10% of medical services involved a gap fee (Australian Prudential Regulation Authority, 2020). The average gap-fee per service was \$20; however, for the 3% of services with no agreed gap, the average was \$448.

assumes there is no moral hazard in the sense that η is not influenced by having private health insurance. Finally, the model is more suited to analysing the choices of singles than families since it only focuses on own risk.

4.3.2 Econometric estimation

Keeping these limitations in mind, I now turn to econometric estimation. I assume people derive utility according to a constant relative risk aversion (CRRA) utility function; $U_i = \frac{(W_i)^{1-\gamma}-1}{1-\gamma}$ where $W_i = Y_i - \pi$ for those with private insurance and $W_i = Y_i$ otherwise. The coefficient of relative risk aversion γ is state dependent and satisfies the following: $\gamma^H \leq \gamma^{S|Q^{PR}} \leq \gamma^{S|Q^{PU}}$. Applying a random utility framework to the value functions in Eq. 2 and Eq. 3, people purchase private insurance if

$$\underbrace{\left[\eta_i \frac{(Y_i-\pi)^{1-\gamma^{S|Q^{PR}}}-1}{1-\gamma^{S|Q^{PR}}} + (1-\eta_i)\frac{(Y_i-\pi)^{1-\gamma^H}-1}{1-\gamma^H}\right]}_{EU_{i,phi=1}} - \underbrace{\left[\eta_i \frac{Y_i^{1-\gamma^{S|Q^{PU}}}-1}{1-\gamma^{S|Q^{PU}}} + (1-\eta_i)\frac{Y_i^{1-\gamma^H}-1}{1-\gamma^H}\right]}_{EU_{i,phi=0}} + \epsilon_i > 0. \tag{4}$$

ϵ_i follows a standard type I extreme value distribution so that Eq. 4 can be estimated as a logistic choice model. The choice probabilities are given by:

$$\Pr(phi=1)_i = \frac{\exp(EU_{i,phi=1} - EU_{i,phi=0})}{1+\exp(EU_{i,phi=1} - EU_{i,phi=0})}. \tag{5}$$

Estimates for the γ's are obtained by maximizing the log-likelihood function:

$$\ln L = \Sigma_{i\in J} \Pr(phi=1)_i + \Sigma_{i\notin J'}(1-\Pr(phi=1)_i) \tag{6}$$

where J is the set of individuals with private health insurance and J' is the set without.

In Eq. 4, premiums π are treated as homogenous and exogenous to insurance demand. A fully structural approach would model premium setting simultaneously to demand, however this is beyond the scope of this paper. Since the goal is demonstration, I further assume that all people face the same premium $\pi = \$1,000$, which, while similar to the annual cost of a basic hospital policy to cover a single adult in 2015, is a fairly arbitrary choice. This also ignores the variation in premiums due to policy incentives (discussed in Appendix C). Household income is only available in bands (see Table A1) and I take income to be the mid-point of these bands. Income is equivalized for families by giving partners 0.5 weight and dependent children 0.3 (similar to the adjustment used by the Australian Bureau of Statistics).

4.3.3 Estimation results

As a baseline I estimate γ^H, $\gamma^{S|Q^{PR}}$ and $\gamma^{S|Q^{PU}}$ without any controls (see Table 5). This model has low internal predictive power, which is unsurprising since the theoretical model implies a positive correlation between risk and insurance and in Figure 8 we saw that this is not the case in the raw data. Standard weighting of the probability function (e.g. Tversky & Kahneman, 1992) cannot resolve this as the relationship does not follow the expected S-shape either. Nevertheless, I re-estimate the model with subjective risk replaced by Tversky and Kahneman (1992)'s weighting function and achieve a modest improvement in model fit and predictive power.[21] Finally, in the third column I condition preferences on some key observables (age, sex, major city, education, couple status, risk willingness) assuming a linear model for preferences $\gamma_i^k = \mathbf{X_i'B^k}$. To capture additional remaining heterogeneity correlated with the subjective preference, I also include a cubic of η_i as a control, although this is obviously endogenous.[22] This model correctly predicts private health insurance choice 63.92% of the time and does a reasonable job at recovering the relationship between insurance

[21] π_i is replaced with $w_i = \pi_i^s/(\pi_i^s + (1-\pi_i^s))^{\frac{1}{s}}$ where s is a parameter to be estimated. Typically, $s < 1$, which gives higher (lower) weight to low (high) probability outcomes.

[22] Other controls and specifications for including η (e.g. as a categorical variable) were also considered but failed to meaningfully improve model fit, or resulted in convergence issues.

and subjective risk in the raw data (see Appendix Figure D1).

Table 5: Structural estimation results

	Parameter estimates		
γ^{H}	0.584	0.555	0.484
$\gamma^{S\|Q^{PR}}$	0.584	0.555	0.619
$\gamma^{S\|Q^{PU}}$	0.590	0.562	0.728
s		0.540	0.232
	Implied welfare losses		
Bad health: private ins.	$0	$0	$30,814
Bad health: public ins.	$3,113	$3,779	$244,853
Quality gap	$3,113	$3,779	$20,583
	Modelling details		
Prob. weighting	No	Yes	Yes
Controls	No	No	Yes
LL	-947.99	-943.44	-856.32
% correctly pred.	55.46	57.91	63.92

Note: See Appendix D for details on the estimation model and full results. For the model with controls, parameter estimates and implied welfare losses are the predicted median values for the sample. % correctly pred. is the percentage of time the model assigns more than 50% probability to the insurance choice actually made.

A major appeal of structural estimation is the ability to perform welfare calculations. Once I allow for heterogeneity in preferences, people with certain attributes have large and disparate γ^{k}'s, which can result in explosively large estimates for the average compensating differentials. For this reason, I report median values (point estimates and standard errors for the model's parameters are reported in Appendix D). I focus on three figures, which relate to Figure 10 in the following way: the monetary compensation to make a person with private hospital insurance indifferent between the bad and good health state ($Y'' - Y'$); indifferent between the bad and good health state for someone relying on Medicare ($Y''' - Y'$); and the difference between these ($Y''' - Y''$), which reflects the compensation needed to make someone in bad health without private insurance indifferent to public or private treatment.[23]

[23]Derivation for these calculations is provided in Appendix D. Note that because I do not impose a restriction that $\gamma^{S|Q^{PR}} \leq \gamma^{S|Q^{PU}}$ in the estimation, this compensation can be negative (i.e. if the person prefers public to private hospital care.)

Without heterogeneity, the utility function for the bad health state is indistinguishable from that for the good health state and there is no compensation needed in this scenario. The compensation needed for the gap in quality of care is \$3,113-\$3,779, which seems low relative to the cost of insurance. This points to the inadequacy of the model without heterogeneity. Allowing for heterogeneity leads to a seemingly more reasonable compensating differential of \$20,583 associated with the quality-gap in hospital care. However, in unreported results I find that the welfare estimates are quite sensitive to the set of control variables. This serves as a reminder that these estimates should be treated as a demonstration of *how* subjective expectations data can be to used in structural research; in particular, obtaining estimates that are reliable for policy making would require better data (ideally with temporal variation).

One lesson from the current exercise is that the quality-gap framework cannot explain private health insurance choices without considerable heterogeneity in preferences. An important question is whether the heterogeneity needed for this model to fit the data is reasonable; in the model allowing for heterogeneity I find that the 75th percentile compensating differential for the quality gap is \$490 million, which is unreasonably large. In calibrating the specifications I also found no clear pattern in how subjective risk correlates with the preference parameters (the γ_i's). This may rule out a simple omitted variable explanation. Another blow to the structural model is that it predicts insurance correctly less often than a simple binary logit model with the same set of controls (64% versus 69%). This evidence motivates developing more sophisticated frameworks than the simple quality-gap framework studied here.

5 Conclusion

This paper provides evidence that people's subjective expectations over broadly defined, common health services, such as hospitalizations and visits to dentists and optometrists, are a high-quality measure of their actual risk. Through a series of examples, I demonstrate the value of collecting these data. Questions on expectations could be included in standard household (ideally longitudinal) surveys at little or no cost.

One important policy implication of this work is that consumers' hold valuable private information over their health service risk. One area that governments could leverage on this is plan selection software for private health insurance. There is a growing literature documenting the ways that consumers fail to select into optimal plans in various health insurance markets (see Stavrunova, 2019, for a review). How to reduce these choice inconsistencies is an ongoing question. If consumers could simply input information on their expected health service use and generate a good recommendation, this could help to overcome the information frictions and biased choice strategies that persevere in these markets. Future research could directly evaluate the merits of this proposal.

There are some limitations of this study worth noting. It is a single study, in a particular institutional environment, and considers a particular set of health services. Some use of the services use will be for preventative and scheduled care; it is likely that expectations over health services with less predictability would be less accurate. Testing the generalizability of the results to other groups of services, in other institutional settings, would therefore be worthwhile.

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Online Appendix

A Additional Tables and Figures

Table A1: Control variables in the Online Survey common to HILDA

Variable	Definition
Age	Age in years
Male	=1 if male
Dep. children	Number of dependent children. A dependent child is classified as a child aged under 18 years (or under 24 years if studying fulltime) who relies on you for maintenance
Employed	=1 if employed (worked in a job, business or farm (or was on some sort of leave from a a job, business or farm) in the last 7 days)
NSW	=1 if lives in New South Wales
VIC	=1 if lives in Victoria
QLD	=1 if lives in Queensland
SA	=1 if lives in South Australia
WA	=1 if lives in Western Australia
TAS	=1 if lives in Tasmania
NT	=1 if lives in Northern Territory
City	=1 if lives in a major city (Sydney, Melbourne, Brisbane, Adelaide, Perth, Canberra)
Inc 0-10K	=1 if household income from all sources for the previous 12 months before tax and other deductions is between \$0–\$9,999
Inc 10-20K	=1 if household income is between \$10,000–\$19,999
Inc 20-30K	=1 if household income is between \$20,000–\$29,999
Inc 30-40K	=1 if household income is between \$30,000–\$39,999
Inc 40-50K	=1 if household income is between \$40,000–\$49,999
Inc 50-60K	=1 if household income is between \$50,000–\$59,999
Inc 60-80K	=1 if household income is between \$60,000–\$79,999
Inc 80-100K	=1 if household income is between \$80,000–\$99,999
Inc 100-125K	=1 if household income is between \$100,000–\$124,999
Inc 125-150K	=1 if household income is between \$125,000–\$149,999
Inc 150-200K	=1 if household income is between \$150,000–\$199,999
Inc 200K+	=1 if household income is between \$200,000 or more
Inc missing	=1 if household income is missing
Edu Degree	=1 if highest level of education is bachelors degree or higher
Married	=1 if married
Defacto	=1 if in a de-facto relationship
Widowed	=1 if widowed
Separated	=1 if separated
SAH Excell	=1 if self-assessed health ‘excellent’

SAH Vgood	=1 if self-assessed health 'very good'
SAH good	=1 if self-assessed health 'good'
SAH Fair	=1 if self-assessed health 'fair'
SAH poor	=1 if self-assessed health 'poor'
PHI	=1 if has private hospital insurance only
PAHI	=1 if has private ancillaries (general treatment) insurance only
PHI both	=1 if has combined private hospital/ancillaries insurance
Risk: None	=1 if self-assessed willingness to take financial risks 'not willing to take any risks'
Risk: Avg.	=1 if self-assessed willingness to take financial risks 'average'
Risk: Ab. avg.	=1 if self-assessed willingness to take financial risks 'above average'
Risk: Substantial	=1 if self-assessed willingness to take financial risks 'substantial'

Table A2: Health service measures in HILDA

Hospital	Admitted to hospital as a day or night patient, or saw a hospital doctor for outpatient or emergency care in last 12 months
Dental	How long has it been since you last saw a dentist? [0-12 months]
Optom	During the last 12 months, have you seen any of these types of health care providers about your health? [Optometrist]
Physical	During the last 12 months, have you seen any of these types of health care providers about your health? [Physiotherapist, chiropractor or osteopath]
Naturo	During the last 12 months, have you seen any of these types of health care providers about your health? [Alternative health practitioner, such as a naturopath, acupuncturist or herbalist]
Massage	N/A

Table A3: Linear regressions on use and expectations

	Hosp		Dentist		Optom	
	Past	Expected	Past	Expected	Past	Expected
Age	-0.036***	-0.023***	-0.001	0.008	-0.012	-0.000
	(0.010)	(0.006)	(0.010)	(0.008)	(0.010)	(0.008)
Age^2	0.000***	0.000***	0.000	-0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.114***	-0.041***	-0.110***	-0.089***	-0.085***	-0.106***
	(0.024)	(0.015)	(0.025)	(0.019)	(0.025)	(0.019)
Dep. children	0.038***	0.028***	0.016	0.016	0.038***	0.017
	(0.013)	(0.009)	(0.013)	(0.010)	(0.014)	(0.011)
Employed	0.010	0.014	-0.009	0.045**	0.035	0.034
	(0.028)	(0.018)	(0.029)	(0.022)	(0.029)	(0.022)

NSW	-0.122	-0.048	-0.047	-0.072	0.129	-0.031
	(0.082)	(0.063)	(0.085)	(0.054)	(0.096)	(0.077)
VIC	-0.119	-0.044	-0.129	-0.135**	0.029	-0.101
	(0.082)	(0.063)	(0.085)	(0.054)	(0.096)	(0.077)
QLD	-0.049	-0.010	-0.075	-0.102*	0.026	-0.029
	(0.084)	(0.064)	(0.087)	(0.055)	(0.097)	(0.078)
SA	-0.070	-0.006	-0.078	-0.094	0.126	-0.013
	(0.087)	(0.066)	(0.091)	(0.059)	(0.101)	(0.081)
WA	-0.080	-0.005	-0.183**	-0.125**	-0.051	-0.122
	(0.090)	(0.067)	(0.093)	(0.060)	(0.103)	(0.082)
TAS	-0.228**	-0.107	0.054	-0.086	0.220*	0.009
	(0.102)	(0.071)	(0.114)	(0.079)	(0.120)	(0.096)
NT	-0.119	-0.121	-0.092	-0.434***	-0.102	-0.414***
	(0.238)	(0.074)	(0.230)	(0.129)	(0.222)	(0.095)
City	-0.041	-0.001	0.114***	0.030	0.040	0.001
	(0.027)	(0.018)	(0.028)	(0.022)	(0.028)	(0.021)
Inc 0-10K	0.031	-0.035	-0.006	-0.204***	-0.231**	-0.131*
	(0.085)	(0.060)	(0.096)	(0.070)	(0.095)	(0.072)
Inc 10-20K	-0.050	-0.011	-0.004	-0.071	-0.134**	-0.044
	(0.065)	(0.043)	(0.067)	(0.052)	(0.067)	(0.050)
Inc 20-30K	-0.083	-0.062	0.043	-0.034	-0.078	-0.061
	(0.058)	(0.038)	(0.060)	(0.046)	(0.060)	(0.046)
Inc 30-40K	-0.174***	-0.026	-0.025	0.005	-0.086	0.020
	(0.052)	(0.035)	(0.059)	(0.044)	(0.058)	(0.044)
Inc 40-50K	0.002	0.000	0.045	-0.091**	-0.028	-0.049
	(0.056)	(0.034)	(0.057)	(0.042)	(0.056)	(0.041)
Inc 50-60K	0.007	0.021	0.030	-0.031	-0.074	-0.009
	(0.056)	(0.036)	(0.055)	(0.042)	(0.056)	(0.043)
Inc 60-80K	0.011	-0.045	0.036	-0.060	-0.123**	-0.022
	(0.049)	(0.030)	(0.050)	(0.037)	(0.049)	(0.037)
Inc 80-100K	-0.097**	-0.051	0.008	-0.058	-0.067	-0.064
	(0.048)	(0.031)	(0.050)	(0.039)	(0.054)	(0.040)
Inc 100-125K	0.019	-0.013	0.021	-0.033	-0.060	-0.021
	(0.053)	(0.034)	(0.050)	(0.039)	(0.053)	(0.040)
Inc 125-150K	-0.086	-0.032	0.124**	0.072*	-0.078	0.035
	(0.054)	(0.034)	(0.054)	(0.042)	(0.058)	(0.044)
Inc 150-200K	-0.022	-0.025	0.112*	0.077*	-0.100	0.020
	(0.060)	(0.040)	(0.058)	(0.046)	(0.061)	(0.049)
Edu Degree	-0.062**	-0.020	0.047	0.033	0.041	0.013
	(0.028)	(0.018)	(0.029)	(0.022)	(0.030)	(0.022)
Married	0.046	0.056***	-0.027	-0.076***	0.068**	0.003
	(0.031)	(0.020)	(0.033)	(0.024)	(0.034)	(0.025)
Defacto	0.061	0.019	-0.053	-0.016	0.025	0.015

	(0.040)	(0.025)	(0.042)	(0.033)	(0.044)	(0.033)
Widowed	0.061	0.009	0.020	-0.118*	-0.033	-0.062
	(0.069)	(0.039)	(0.080)	(0.070)	(0.083)	(0.058)
Separated	0.133**	0.049	-0.003	-0.031	0.010	-0.005
	(0.059)	(0.038)	(0.056)	(0.042)	(0.058)	(0.043)
SAH Excell	-0.356***	-0.388***	0.168***	0.029	-0.033	-0.103*
	(0.067)	(0.046)	(0.065)	(0.053)	(0.067)	(0.054)
SAH Vgood	-0.398***	-0.368***	0.153***	0.027	-0.057	-0.142***
	(0.056)	(0.043)	(0.054)	(0.045)	(0.057)	(0.045)
SAH good	-0.297***	-0.270***	0.121**	0.034	-0.021	-0.093**
	(0.056)	(0.043)	(0.053)	(0.044)	(0.056)	(0.045)
SAH Fair	-0.196***	-0.166***	0.125**	0.043	0.035	-0.025
	(0.060)	(0.045)	(0.057)	(0.046)	(0.059)	(0.047)
PHI	0.067	0.046	0.214***	0.126***	0.119**	0.072*
	(0.051)	(0.030)	(0.056)	(0.039)	(0.058)	(0.038)
PAHI	-0.036	0.008	0.303***	0.284***	0.120**	0.156***
	(0.046)	(0.033)	(0.048)	(0.037)	(0.054)	(0.040)
PHI both	0.011	0.002	0.272***	0.268***	0.227***	0.194***
	(0.028)	(0.018)	(0.029)	(0.023)	(0.029)	(0.022)
Risk: Avg.	-0.117	-0.040	-0.029	0.040	0.079	0.069
	(0.083)	(0.050)	(0.080)	(0.070)	(0.079)	(0.061)
Risk: Ab. avg.	-0.153*	-0.082*	-0.048	0.073	-0.017	0.087
	(0.079)	(0.047)	(0.075)	(0.068)	(0.074)	(0.058)
Risk: Substantial	-0.196**	-0.120**	-0.116	0.003	0.007	0.051
	(0.079)	(0.047)	(0.076)	(0.068)	(0.075)	(0.059)
Constant	1.694***	1.084***	0.290	0.177	0.348	0.263
	(0.251)	(0.163)	(0.259)	(0.191)	(0.265)	(0.199)
Observations	1,528	1,528	1,528	1,528	1,528	1,528
R^2	0.106	0.148	0.165	0.217	0.142	0.167
Hausman χ^2 (P-val)	(0.004)		(0.002)		(0.000)	

Note: For each health service, the left column reports OLS estimates on a dummy for whether the person visited the relevant health care provider in the last 12 months. The right column reports OLS estimates on the subjective probability of visiting the relevant health care provider in the next 12 months. The Hausman tests are on the joint equality of the left and right column coefficients excluding constants. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Linear regressions on use and expectations

	Physical		Naturo		Massage	
	Past	Expected	Past	Expected	Past	Expected
Age	-0.021**	-0.011	-0.013***	-0.006*	-0.005	-0.005
	(0.009)	(0.007)	(0.005)	(0.004)	(0.008)	(0.006)
Age^2	0.000**	0.000	0.000**	0.000	0.000	0.000

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.074***	-0.068***	-0.035***	-0.043***	-0.095***	-0.061***
	(0.023)	(0.017)	(0.011)	(0.010)	(0.020)	(0.016)
Dep. children	0.010	0.014	0.011	0.012**	0.018	0.006
	(0.013)	(0.009)	(0.007)	(0.006)	(0.011)	(0.008)
Employed	0.053**	0.032*	-0.001	0.007	0.055**	0.051***
	(0.026)	(0.019)	(0.013)	(0.011)	(0.022)	(0.017)
NSW	-0.011	-0.020	-0.006	0.030	-0.054	0.012
	(0.091)	(0.069)	(0.050)	(0.025)	(0.083)	(0.062)
VIC	-0.025	-0.013	-0.001	0.037	-0.052	0.003
	(0.092)	(0.070)	(0.051)	(0.025)	(0.083)	(0.062)
QLD	0.022	0.023	0.001	0.039	0.013	0.054
	(0.093)	(0.070)	(0.051)	(0.025)	(0.084)	(0.063)
SA	0.005	0.038	-0.035	0.039	-0.083	0.011
	(0.096)	(0.074)	(0.051)	(0.028)	(0.086)	(0.065)
WA	-0.025	0.015	-0.023	0.026	-0.109	-0.005
	(0.098)	(0.074)	(0.053)	(0.028)	(0.088)	(0.067)
TAS	0.065	-0.003	-0.029	-0.017	0.036	0.030
	(0.118)	(0.085)	(0.051)	(0.027)	(0.106)	(0.074)
NT	0.023	0.010	-0.048	0.075	-0.163*	0.024
	(0.243)	(0.150)	(0.058)	(0.090)	(0.094)	(0.130)
City	0.020	0.024	0.027**	0.015	0.051**	0.038**
	(0.026)	(0.019)	(0.011)	(0.011)	(0.021)	(0.016)
Inc 0-10K	-0.021	-0.015	0.021	-0.004	0.012	-0.003
	(0.077)	(0.066)	(0.018)	(0.028)	(0.066)	(0.054)
Inc 10-20K	0.046	0.007	0.028	0.032	0.017	0.014
	(0.059)	(0.040)	(0.021)	(0.020)	(0.047)	(0.036)
Inc 20-30K	0.023	0.003	0.036*	0.028	0.009	0.026
	(0.052)	(0.037)	(0.021)	(0.022)	(0.041)	(0.034)
Inc 30-40K	0.033	0.051	0.009	0.023	-0.004	0.025
	(0.053)	(0.036)	(0.015)	(0.020)	(0.042)	(0.034)
Inc 40-50K	-0.015	-0.042	0.069**	0.015	0.021	-0.018
	(0.052)	(0.034)	(0.027)	(0.020)	(0.047)	(0.033)
Inc 50-60K	0.064	0.044	0.105***	0.044**	0.060	0.034
	(0.053)	(0.038)	(0.028)	(0.020)	(0.046)	(0.035)
Inc 60-80K	0.017	-0.022	0.019	-0.011	-0.056	-0.056*
	(0.046)	(0.032)	(0.017)	(0.016)	(0.038)	(0.030)
Inc 80-100K	0.016	0.014	0.022	0.027	-0.011	-0.007
	(0.049)	(0.035)	(0.019)	(0.020)	(0.044)	(0.034)
Inc 100-125K	-0.003	0.022	0.053**	0.023	-0.004	-0.013
	(0.049)	(0.035)	(0.024)	(0.021)	(0.044)	(0.034)
Inc 125-150K	-0.075	0.027	0.035	0.042*	-0.009	0.029
	(0.054)	(0.040)	(0.025)	(0.025)	(0.051)	(0.041)

Inc 150-200K	0.068	0.040	0.014	0.023	-0.016	0.005
	(0.064)	(0.046)	(0.025)	(0.026)	(0.054)	(0.043)
Edu Degree	-0.017	-0.025	0.011	-0.027**	-0.018	-0.024
	(0.029)	(0.021)	(0.015)	(0.012)	(0.025)	(0.019)
Married	0.034	-0.026	-0.007	-0.002	0.009	0.006
	(0.031)	(0.022)	(0.015)	(0.013)	(0.026)	(0.019)
Defacto	0.026	-0.025	-0.015	-0.018	0.016	0.009
	(0.039)	(0.028)	(0.019)	(0.016)	(0.035)	(0.027)
Widowed	0.087	0.022	0.006	0.016	0.089	0.075
	(0.077)	(0.059)	(0.037)	(0.027)	(0.068)	(0.047)
Separated	0.062	0.033	-0.000	0.003	0.032	0.036
	(0.056)	(0.040)	(0.022)	(0.021)	(0.045)	(0.037)
SAH Excell	-0.096	-0.132***	0.052*	0.020	-0.025	-0.033
	(0.064)	(0.047)	(0.029)	(0.027)	(0.055)	(0.044)
SAH Vgood	-0.136***	-0.131***	0.022	-0.026	-0.043	-0.047
	(0.052)	(0.038)	(0.016)	(0.018)	(0.044)	(0.035)
SAH good	-0.112**	-0.115***	0.013	-0.014	-0.036	-0.038
	(0.051)	(0.038)	(0.015)	(0.018)	(0.043)	(0.034)
SAH Fair	-0.082	-0.059	0.026	0.007	-0.029	-0.025
	(0.054)	(0.040)	(0.017)	(0.019)	(0.044)	(0.034)
PHI	0.147***	0.077**	0.062**	0.031*	0.104**	0.040
	(0.051)	(0.032)	(0.029)	(0.018)	(0.043)	(0.029)
PAHI	0.226***	0.196***	0.027	0.021	0.148***	0.110***
	(0.051)	(0.038)	(0.024)	(0.018)	(0.045)	(0.035)
PHI both	0.188***	0.188***	0.022*	0.055***	0.109***	0.102***
	(0.027)	(0.019)	(0.012)	(0.010)	(0.023)	(0.018)
Risk: Avg.	0.016	0.034	-0.009	0.006	-0.032	-0.040
	(0.078)	(0.048)	(0.051)	(0.036)	(0.076)	(0.059)
Risk: Ab. avg.	-0.101	0.007	-0.071	-0.029	-0.125*	-0.065
	(0.073)	(0.044)	(0.047)	(0.034)	(0.072)	(0.056)
Risk: Substantial	-0.114	-0.010	-0.082*	-0.058*	-0.153**	-0.121**
	(0.073)	(0.045)	(0.046)	(0.034)	(0.071)	(0.056)
Constant	0.748***	0.463***	0.334***	0.226**	0.405*	0.358**
	(0.241)	(0.176)	(0.126)	(0.095)	(0.209)	(0.162)
Observations	1,528	1,528	1,528	1,528	1,528	1,528
R^2	0.082	0.119	0.078	0.086	0.087	0.092
Hausman χ^2 (P-val)	(0.009)		(0.004)		(0.151)	

Note: See Table A3.

Table A5: Linear regressions on use and expectations: Childless singles only

	Hosp		Dentist		Optom	

	Past	Expected	Past	Expected	Past	Expected
Age	-0.030*	-0.011	-0.027	0.011	-0.012	0.013
	(0.015)	(0.009)	(0.017)	(0.012)	(0.017)	(0.013)
Age^2	0.000**	0.000	0.000*	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.096**	-0.076***	-0.103**	-0.120***	-0.087*	-0.116***
	(0.044)	(0.027)	(0.048)	(0.037)	(0.048)	(0.035)
Employed	-0.004	-0.047	-0.032	0.017	0.024	0.032
	(0.050)	(0.031)	(0.054)	(0.043)	(0.052)	(0.043)
NSW	-0.121	-0.008	-0.256**	-0.191***	0.124	-0.027
	(0.150)	(0.092)	(0.107)	(0.068)	(0.168)	(0.152)
VIC	-0.107	0.008	-0.319***	-0.259***	0.060	-0.098
	(0.150)	(0.094)	(0.107)	(0.068)	(0.169)	(0.153)
QLD	0.002	-0.031	-0.192*	-0.223***	0.073	-0.017
	(0.157)	(0.095)	(0.112)	(0.074)	(0.170)	(0.154)
SA	0.043	0.003	-0.250**	-0.195**	0.169	-0.060
	(0.164)	(0.100)	(0.127)	(0.084)	(0.178)	(0.160)
WA	-0.107	-0.012	-0.385***	-0.312***	-0.068	-0.198
	(0.163)	(0.102)	(0.127)	(0.086)	(0.177)	(0.158)
TAS	-0.200	-0.087	-0.055	-0.206	0.323	0.119
	(0.198)	(0.107)	(0.164)	(0.134)	(0.211)	(0.171)
NT	-0.134	-0.024	-0.405	-0.610***	-0.274	-0.320*
	(0.201)	(0.111)	(0.258)	(0.106)	(0.241)	(0.174)
City	-0.032	-0.004	0.055	0.026	0.066	0.006
	(0.045)	(0.027)	(0.050)	(0.039)	(0.048)	(0.037)
Inc 0-10K	0.064	0.021	0.096	-0.112	0.010	-0.117
	(0.116)	(0.085)	(0.147)	(0.106)	(0.146)	(0.108)
Inc 10-20K	-0.056	0.086	0.131	0.042	-0.098	-0.057
	(0.092)	(0.059)	(0.099)	(0.077)	(0.099)	(0.072)
Inc 20-30K	-0.063	-0.004	0.238**	0.104	-0.056	-0.059
	(0.083)	(0.055)	(0.094)	(0.075)	(0.094)	(0.074)
Inc 30-40K	-0.082	0.010	0.029	-0.035	-0.035	-0.094
	(0.084)	(0.050)	(0.097)	(0.078)	(0.093)	(0.069)
Inc 40-50K	-0.042	-0.014	0.098	-0.071	-0.059	-0.149**
	(0.099)	(0.050)	(0.110)	(0.077)	(0.102)	(0.075)
Inc 50-60K	0.078	0.119**	0.076	0.013	0.033	0.008
	(0.105)	(0.057)	(0.107)	(0.081)	(0.109)	(0.079)
Inc 60-80K	0.019	0.023	0.182*	-0.040	-0.128	-0.119*
	(0.084)	(0.047)	(0.095)	(0.069)	(0.094)	(0.065)
Inc 80-100K	-0.111	-0.027	0.173	-0.087	0.023	-0.214***
	(0.092)	(0.051)	(0.108)	(0.087)	(0.120)	(0.081)
Inc 100-125K	0.110	0.130*	0.012	-0.077	0.145	-0.059
	(0.115)	(0.071)	(0.116)	(0.097)	(0.129)	(0.095)

Inc 125-150K	0.097	0.086	0.346***	0.165	0.042	-0.052
	(0.130)	(0.083)	(0.116)	(0.102)	(0.142)	(0.110)
Inc 150-200K	-0.011	0.032	0.040	0.046	-0.026	0.023
	(0.119)	(0.074)	(0.140)	(0.096)	(0.141)	(0.098)
Edu Degree	-0.214***	-0.101***	0.025	0.030	-0.015	-0.020
	(0.045)	(0.029)	(0.056)	(0.042)	(0.057)	(0.042)
SAH Excell	-0.144	-0.274***	0.165	0.031	0.064	-0.060
	(0.109)	(0.068)	(0.118)	(0.092)	(0.106)	(0.089)
SAH Vgood	-0.227**	-0.205***	0.205**	0.156**	0.134	-0.046
	(0.093)	(0.066)	(0.100)	(0.076)	(0.086)	(0.076)
SAH good	-0.160*	-0.187***	0.112	0.078	0.159*	-0.006
	(0.091)	(0.065)	(0.095)	(0.073)	(0.082)	(0.073)
SAH Fair	-0.023	-0.093	0.127	0.125*	0.171*	0.016
	(0.097)	(0.070)	(0.096)	(0.074)	(0.088)	(0.073)
PHI	0.059	0.048	0.233**	0.115*	0.129	-0.054
	(0.080)	(0.040)	(0.097)	(0.069)	(0.092)	(0.061)
PAHI	-0.058	-0.013	0.303***	0.374***	0.209**	0.198***
	(0.065)	(0.044)	(0.079)	(0.063)	(0.088)	(0.068)
PHI both	0.092*	0.022	0.267***	0.263***	0.247***	0.166***
	(0.050)	(0.032)	(0.053)	(0.042)	(0.055)	(0.041)
Risk: Avg.	-0.159	-0.003	0.095	0.087	0.089	-0.071
	(0.198)	(0.081)	(0.196)	(0.171)	(0.150)	(0.157)
Risk: Ab. avg.	-0.129	0.021	0.119	0.121	0.008	0.020
	(0.195)	(0.078)	(0.189)	(0.167)	(0.142)	(0.152)
Risk: Substantial	-0.201	-0.027	-0.047	-0.021	0.011	-0.078
	(0.195)	(0.080)	(0.189)	(0.166)	(0.141)	(0.151)
Constant	1.329***	0.648***	0.887*	0.244	0.100	0.137
	(0.448)	(0.244)	(0.460)	(0.330)	(0.450)	(0.370)
Observations	482	482	482	482	482	482
R^2	0.131	0.152	0.198	0.259	0.160	0.184
Hausman χ^2 (P-val)	(0.035)		(0.122)		(0.279)	

Note: See Table A3.

Table A6: Linear regressions on use and expectations: Childless singles only

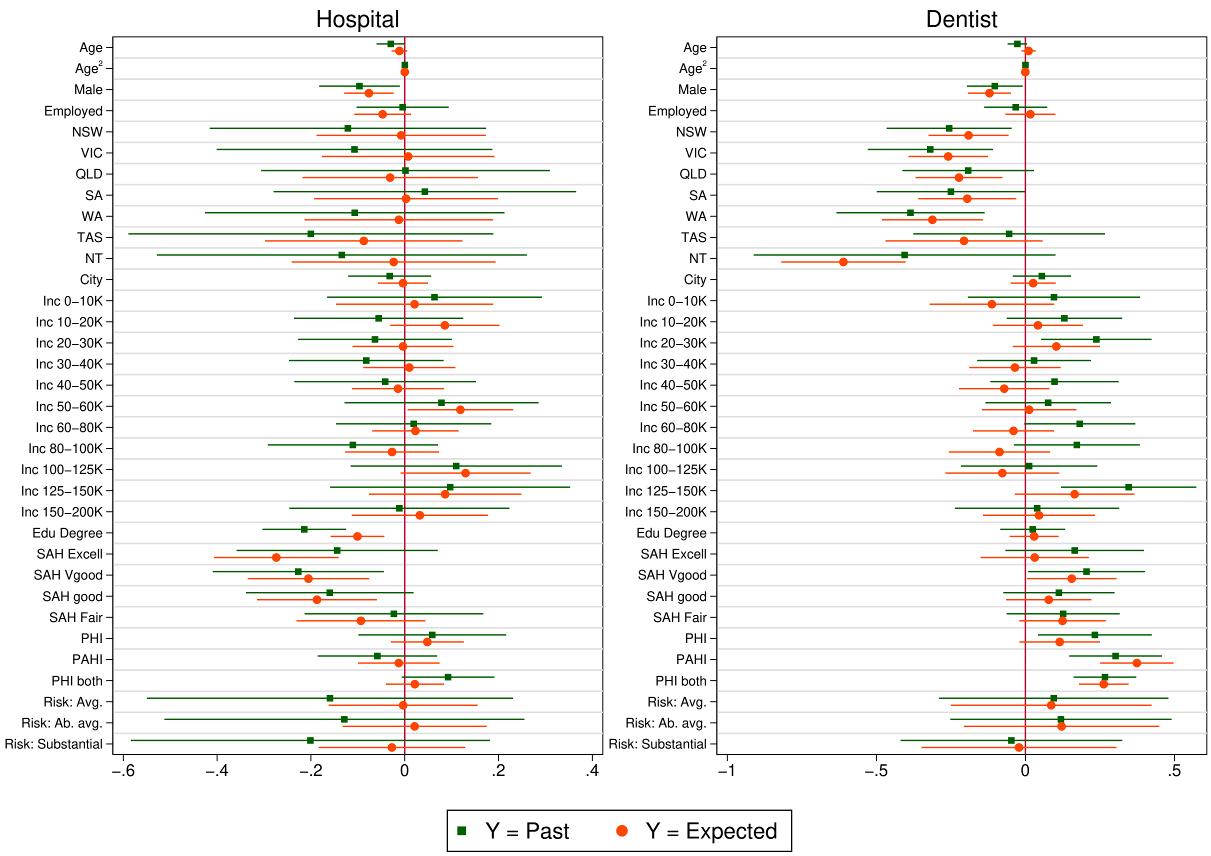
	Physical		Naturo		Massage	
	Past	Expected	Past	Expected	Past	Expected
Age	-0.008	0.004	-0.009	0.007	-0.005	0.006
	(0.013)	(0.010)	(0.008)	(0.006)	(0.012)	(0.010)
Age^2	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Male	-0.099**	-0.111***	-0.027	-0.043***	-0.148***	-0.113***
	(0.043)	(0.031)	(0.019)	(0.016)	(0.036)	(0.029)
Employed	0.042	0.007	-0.014	-0.011	0.018	0.042
	(0.044)	(0.034)	(0.019)	(0.018)	(0.036)	(0.031)
NSW	0.109	0.075	-0.047	0.023	-0.056	-0.051
	(0.100)	(0.098)	(0.090)	(0.046)	(0.120)	(0.122)
VIC	0.084	0.041	-0.013	0.026	-0.055	-0.066
	(0.102)	(0.099)	(0.093)	(0.047)	(0.123)	(0.124)
QLD	0.165	0.113	-0.008	0.019	0.014	-0.023
	(0.104)	(0.100)	(0.091)	(0.046)	(0.126)	(0.125)
SA	0.195	0.098	-0.038	0.010	-0.094	-0.116
	(0.119)	(0.111)	(0.095)	(0.049)	(0.127)	(0.127)
WA	0.099	0.075	-0.023	0.001	-0.075	-0.047
	(0.117)	(0.107)	(0.093)	(0.048)	(0.128)	(0.131)
TAS	0.087	0.081	-0.054	-0.020	0.040	-0.080
	(0.154)	(0.133)	(0.091)	(0.050)	(0.165)	(0.136)
NT	-0.140	-0.050	-0.112	-0.029	-0.274	-0.184
	(0.240)	(0.157)	(0.120)	(0.074)	(0.201)	(0.141)
City	0.032	0.066**	0.036**	0.016	0.088***	0.063**
	(0.044)	(0.031)	(0.015)	(0.018)	(0.033)	(0.027)
Inc 0-10K	-0.100	-0.082	0.035	-0.021	-0.047	-0.111**
	(0.080)	(0.067)	(0.035)	(0.026)	(0.064)	(0.053)
Inc 10-20K	0.058	0.032	0.036	0.045	0.007	-0.010
	(0.083)	(0.059)	(0.032)	(0.029)	(0.067)	(0.056)
Inc 20-30K	0.011	0.030	0.030	0.026	0.001	0.020
	(0.078)	(0.057)	(0.030)	(0.027)	(0.067)	(0.057)
Inc 30-40K	0.072	0.018	-0.003	-0.012	0.018	-0.028
	(0.084)	(0.059)	(0.025)	(0.025)	(0.073)	(0.061)
Inc 40-50K	0.053	-0.050	0.085*	0.012	0.134	-0.001
	(0.090)	(0.060)	(0.047)	(0.035)	(0.085)	(0.064)
Inc 50-60K	0.168*	0.125	0.118**	0.054	0.115	0.035
	(0.098)	(0.077)	(0.053)	(0.038)	(0.088)	(0.071)
Inc 60-80K	0.017	-0.039	0.048	-0.006	-0.043	-0.106*
	(0.077)	(0.052)	(0.034)	(0.025)	(0.068)	(0.056)
Inc 80-100K	0.145	0.073	0.053	0.050	0.048	-0.063
	(0.105)	(0.078)	(0.052)	(0.050)	(0.101)	(0.071)
Inc 100-125K	-0.064	0.005	0.044	0.076	-0.094	-0.054
	(0.103)	(0.080)	(0.067)	(0.062)	(0.085)	(0.082)
Inc 125-150K	-0.051	0.016	0.035	0.102	-0.079	-0.025
	(0.114)	(0.095)	(0.068)	(0.073)	(0.084)	(0.086)
Inc 150-200K	-0.033	-0.013	-0.026	0.005	-0.045	-0.014
	(0.122)	(0.092)	(0.030)	(0.038)	(0.103)	(0.100)
Edu Degree	-0.110**	-0.055	-0.007	-0.033	-0.087**	-0.067*

	(0.052)	(0.039)	(0.027)	(0.022)	(0.043)	(0.036)
SAH Excell	0.049	-0.019	0.098*	0.018	0.147	0.007
	(0.113)	(0.083)	(0.055)	(0.046)	(0.090)	(0.070)
SAH Vgood	-0.110	-0.022	0.046**	0.024	0.031	0.037
	(0.090)	(0.063)	(0.023)	(0.026)	(0.066)	(0.052)
SAH good	-0.115	-0.058	0.026	-0.009	0.013	0.001
	(0.087)	(0.061)	(0.018)	(0.025)	(0.062)	(0.050)
SAH Fair	-0.074	0.009	0.026	0.011	0.023	0.014
	(0.093)	(0.066)	(0.021)	(0.027)	(0.066)	(0.051)
PHI	0.153*	0.034	0.089**	0.029	0.182**	0.101*
	(0.083)	(0.053)	(0.044)	(0.024)	(0.077)	(0.057)
PAHI	0.197**	0.233***	-0.026*	0.002	0.128*	0.126**
	(0.077)	(0.064)	(0.014)	(0.021)	(0.067)	(0.060)
PHI both	0.226***	0.167***	0.036*	0.048***	0.090**	0.084***
	(0.048)	(0.036)	(0.019)	(0.018)	(0.040)	(0.031)
Risk: Avg.	0.144	0.067	-0.003	-0.007	0.035	0.067
	(0.141)	(0.101)	(0.118)	(0.090)	(0.142)	(0.073)
Risk: Ab. avg.	0.085	0.079	-0.060	-0.005	0.010	0.116*
	(0.135)	(0.097)	(0.116)	(0.089)	(0.137)	(0.067)
Risk: Substantial	0.062	0.037	-0.064	-0.015	-0.024	0.060
	(0.136)	(0.097)	(0.115)	(0.090)	(0.136)	(0.068)
Constant	0.159	-0.038	0.255	-0.059	0.241	0.025
	(0.346)	(0.266)	(0.217)	(0.165)	(0.314)	(0.266)
Observations	482	482	482	482	482	482
R^2	0.151	0.167	0.128	0.098	0.162	0.139
Hausman χ^2 (P-val)	(0.067)		(0.018)		(0.007)	

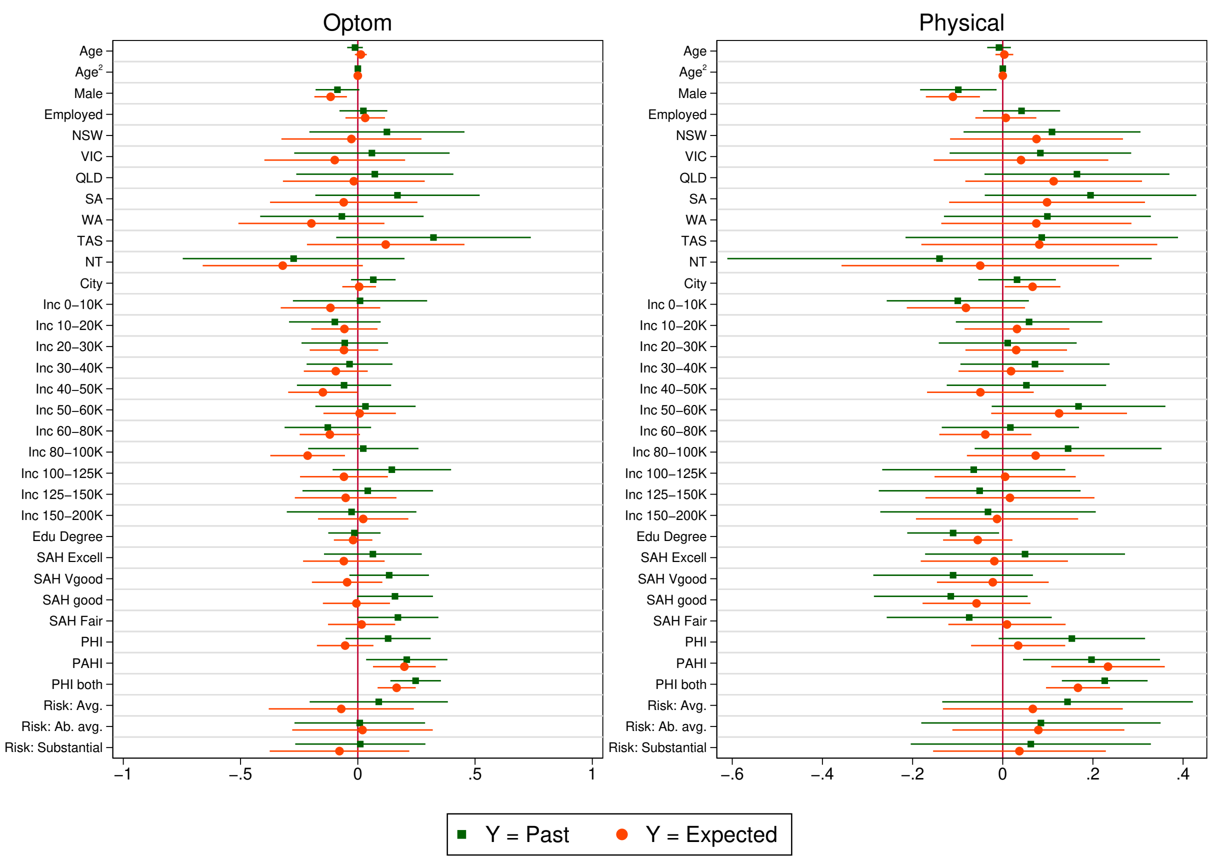
Note: See Table A3.

Figure A1: Coefficient estimates childless singles – Hospital and Dentist use



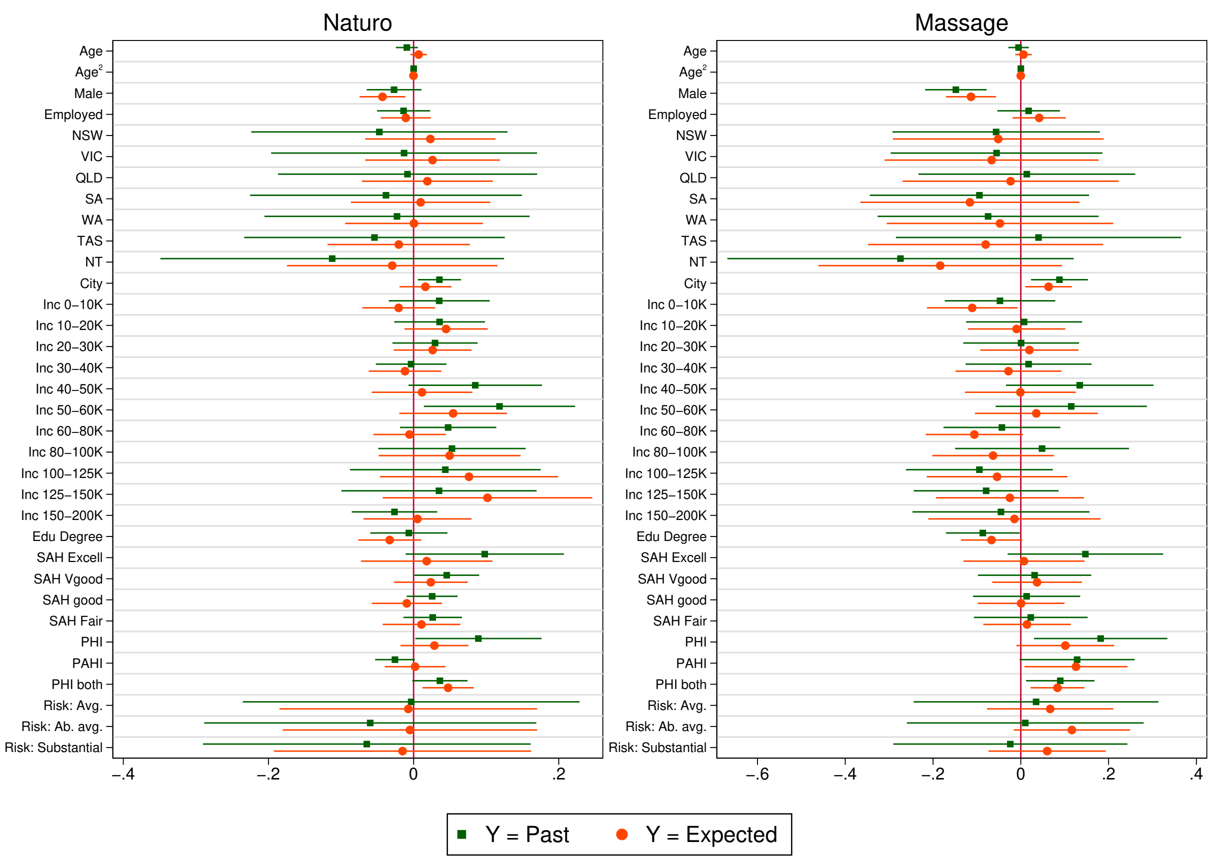
Note: Displayed are coefficient estimates and 95% confidence intervals (robust standard errors) from linear regression on an indicator for actual health service use in the last 12 months (squares) and expected probability of health service use in the next 12 months (circles). n=1,528.

Figure A2: Coefficient estimates childless singles – Optom and Physical use



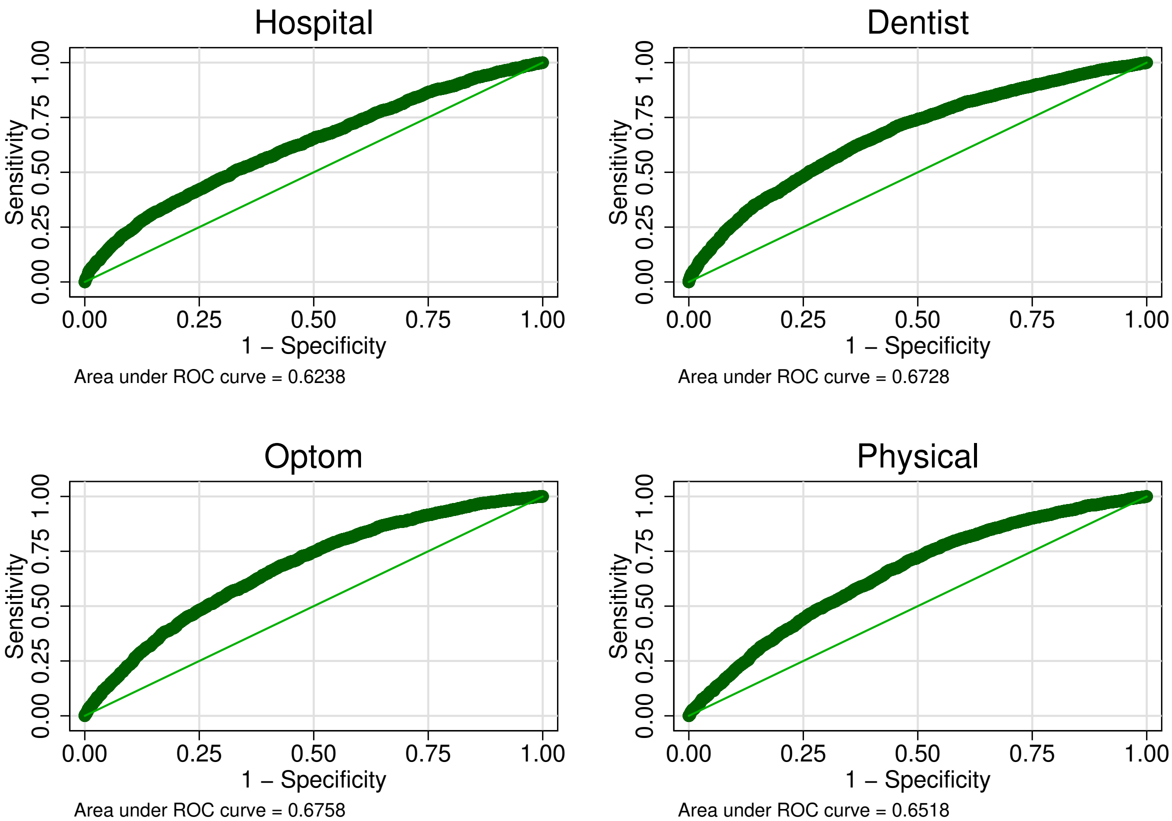
Note: See Figure A1

Figure A3: Coefficient estimates childless singles – Naturo and Massage use



Note: See Figure A1

Figure A4: ROC curves



Note: The ROC curves are based on lasso logit estimates using the 2013 wave of HILDA. The tuning parameter was selected using K-fold cross validation and the preferred subset of covariates chosen based on a lowest deviance criterion. Sensitivity is the fraction of correctly identified positive outcome cases; specificity is one minus the fraction of correctly identified negative outcome cases. The area between the ROC curve and the 45 degree line (the ROC curve in a model with no predictive power) gives a measure of model fit ranging from 0 to 1, with higher values indicating better fit.

B Comparison between health service utilization variables in Online Survey and HILDA

As discussed in Section 2, because people are asked about health service visits generally in the Online Survey, it is possible that some of the variation in responses (to both subjective expectations and health service use in the last 12 months) is on behalf of other persons (e.g. spouses, children). To explore this, I compare the frequencies of reported health service utilization between the Online Survey and HILDA. Table B1 reports the raw differences and the differences after adjusting for covariates using propensity score matching.

Table B1: Mean utilization in Online Survey and HILDA

	Mean		Difference	
	Online sample	HILDA	Raw	Conditional
Hospital	0.317	0.270	0.048***	0.057***
			(0.012)	(0.021)
N	1,528	10,610	12,138	10,833
Hospital (no emergency)	0.317	0.204	0.113***	0.124***
			(0.011)	(0.020)
N	1,528	10,609	12,137	10,832
Dentist	0.573	0.532	0.042***	0.036*
			(0.014)	(0.019)
N	1,528	11,096	12,624	10,832
Optom	0.477	0.263	0.214***	0.212***
			(0.012)	(0.019)
N	1,528	10,612	12,140	10,834
Physical	0.270	0.252	0.018	0.015
			(0.012)	(0.019)
N	1,528	11,096	12,624	10,890

Note: Conditional differences are based on propensity score estimates using a logit model to predict selection into the experimental sample. Controls are the variables in Table A1. Robust Abadie-Imbens standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Reported frequencies for hospitalizations and optometrist visits are higher in the Online Survey, which is consistent with responses being partially on behalf of others. However, visits to dentists are only significant at 10% after conditioning on observables; differences for physical health services are small and insignificant. In HILDA, people are specifically told not to include emergency care as part of self-reported hospital admissions (they are then asked about emergency visits separately). There is no such restriction in the Online survey, and the smaller gap when emergency care is included in the HILDA hospitalization variable indicates that people did include emergency visits in their reported hospital use in the Online Survey.

If people are reporting on behalf of others, this is most likely to manifest in families, with people reporting on behalf of spouses and children. This suggests focussing on singles if we want measures of expectations and prior utilization that reflect personal care only. To explore this I repeat the comparisons in Table B1 for singles only (see Table B2).

Table B2: Mean utilization in Online Survey and HILDA: Singles only

	Mean		Difference	
	Online sample	HILDA	Raw	Conditional
Hospital	0.256	0.276	-0.021	-0.018
			(0.022)	(0.028)
N	1,528	2,143	2,625	2,246
Hospital	0.256	0.191	0.064***	0.073***
(no emergency)			(0.020)	(0.027)
N	482	2,142	2,624	2,245
Dentist	0.527	0.469	0.058**	-0.023
			(0.025)	(0.029)
N	482	2,383	2,865	2,253
Optom	0.383	0.254	0.129***	0.123***
			(0.022)	(0.031)
N	482	2,144	2,626	2,247
Physical	0.226	0.212	0.014	0.009
			(0.020)	(0.028)
N	482	2,383	2,865	2,253

Note: See Table B1

After restricting attention to singles, differences between samples shrink, and only the difference for optometry remains significant after matching. People may understate their visits to optometrists in HILDA because they are asked whether they visited an optometrist about their *health* (see Table A2). A common reason people visit optometrists in Australia is to purchase new corrective eyewear, which can be a purely cosmetic choice. People may have ignored these visits when responding to the HILDA survey. In practice, it is not clear whether we should want people to include or exclude visits that do not involve a clinical consultation. From the perspective of private health insurance, the main cost incurred by insurers are replacement of corrective eyewear (e.g. glasses and frames). Insurers can incur these costs regardless of whether there is a clinical consultation.

Overall, the results indicate that if we restrict the sample to singles, responses in the Online Survey are likely to predominately reflect own expected and actual health service use.

C Policy incentives and correlations between risk and insurance

In Section 4.1, I plot the relationships between subjective expectations and private health insurance for each of the health services. Here I explore how these relationships are affected by i) heterogeneity in risk preferences and ii) heterogeneity in age, income and family composition, which are expected to affect demand for insurance in part because of policy incentives.

C.1 Policy incentives

Three major incentives to purchase private health insurance operate in Australia:

- **Private health insurance premium rebate**. The rebate was originally a universal subsidy of 30% of the premium. Since the 2012-13 financial year, the rebate has been means tested. In the year the Online Survey data were collected (2015), the rebate was approximately 28% for singles (couples) with income (combined income) less than AUD$90,000 (AUD$180,000).

- **Medicare levy surcharge (MLS)**. The MLS is a tax mandate whereby people who earn more than the MLS threshold pay an additional tax on their taxable income if they (or their dependants) are not covered by a complying private hospital cover policy (or are otherwise exempt, e.g. defence force members). The MLS rates are means tested and linked to reductions in the premium rebate. The tax/rebate schedule that applied in the 2015-16 financial year is below.

	Base tier	Tier 1	Tier 2	Tier 3
Single	$\leq \$90,000$	$\$90,001$ – $\$105,000$	$\$105,001$ – $\$140,000$	$\geq \$140,001$
Family	$\leq \$180,000$	$\$180,001$ – $\$210,000$	$\$210,001$ – $\$280,000$	$\geq \$280,001$
MLS rate	0%	1%	1.25%	1.5%
Premium rebates (December 2015)				
<65 years	27.820%	18.547%	9.273%	0%
65-69 years	32.457%	23.184%	13.910%	0%
≥70 years	37.094%	27.820%	18.547%	0%

Note: Families include couples (married or defacto) and single parents. For families with two or more dependent children, the family income threshold is increased by $1,500 for each dependent child after the first child. Age rules on the premium rebate are based on the oldest person covered by the policy.

- **Lifetime health cover (LHC) loading**. Consumers must pay a loading of 2% for every year they were not covered by a complying private hospital insurance policy after their 31st birthday. LHC loading is capped at 70% and is removed after a period of 10 years of continuous coverage.

C.2 Risk preferences

The Online Survey includes two measures of risk preference. The first is stated willingness to take risk with investment income. Participants are asked:

> Which of the following statements comes closest to describing the amount of financial risk that you are willing to take with your spare cash? That is, cash used for savings or investment.

Participants can choose from the following responses (emphasis not added).

1. I take <u>substantial</u> financial risks expecting to earn substantial returns
2. I take <u>above-average</u> financial risks expecting to earn above-average returns
3. I take <u>average</u> financial risks expecting to earn average returns
4. I am not willing to take <u>any</u> financial risks
5. I never have any spare cash

People who choose option 5 are given the following follow-up question.

> Assume you had some spare cash that could be used for savings or investment. Which of the following statements comes closest to describing the amount of financial risk that you would be willing to take with this money?

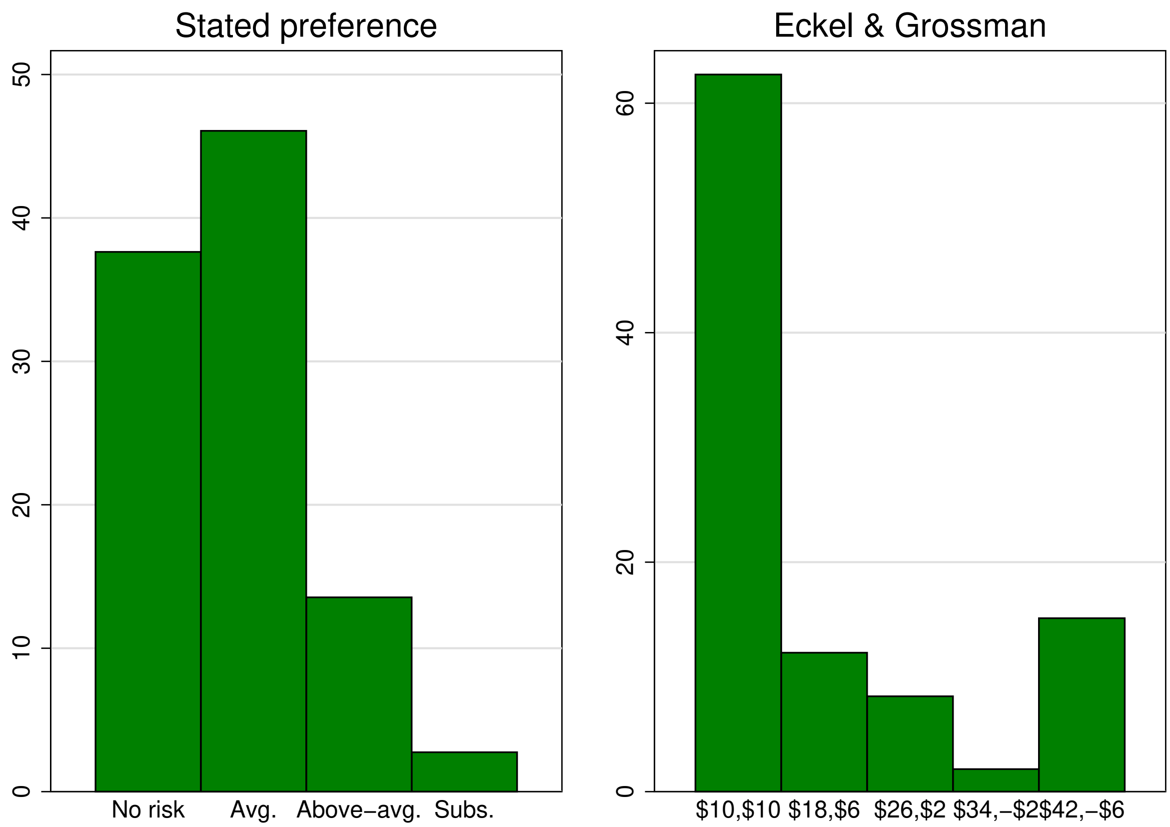
They are then asked to choose from 1-4 above. This measure of risk preference is also contained in the HILDA survey and its validity is assessed in Kettlewell (2019a), who finds it has the expected correlations with covariates like age and gender, strongly predicts risk taking behaviors (owning dividends, equity share of wealth, investment property, self-employment) and correlates reasonably strongly with an experimentally validated stated risk preference measure.

The second measure is a hypothetical version of the Eckel and Grossman (2002) lottery choice task. Participants are asked to consider five hypothetical 50/50 lotteries and choose their preferred option. The lottery options and choice distribution are in Figure C1.

C.3 Residualized correlations

To net-out the effect of risk preferences and policy incentives from the correlation plots between subjective expectations and private health insurance, I estimate linear regressions with insurance as the dependent variable and risk preference, age, income and family status as controls. Because the MLS and premium rebate depend on family status, I control for being in a couple (married or de-facto) and all categories for household income (see Table A1) are interacted with a dummy for being in a couple (these interactions are dropped in the models that only include childless singles). Risk preferences are flexibly controlled for by including full factorials for each of the risk preference tasks. Age is controlled for using a quadratic function. The sample mean level of private health insurance coverage is added

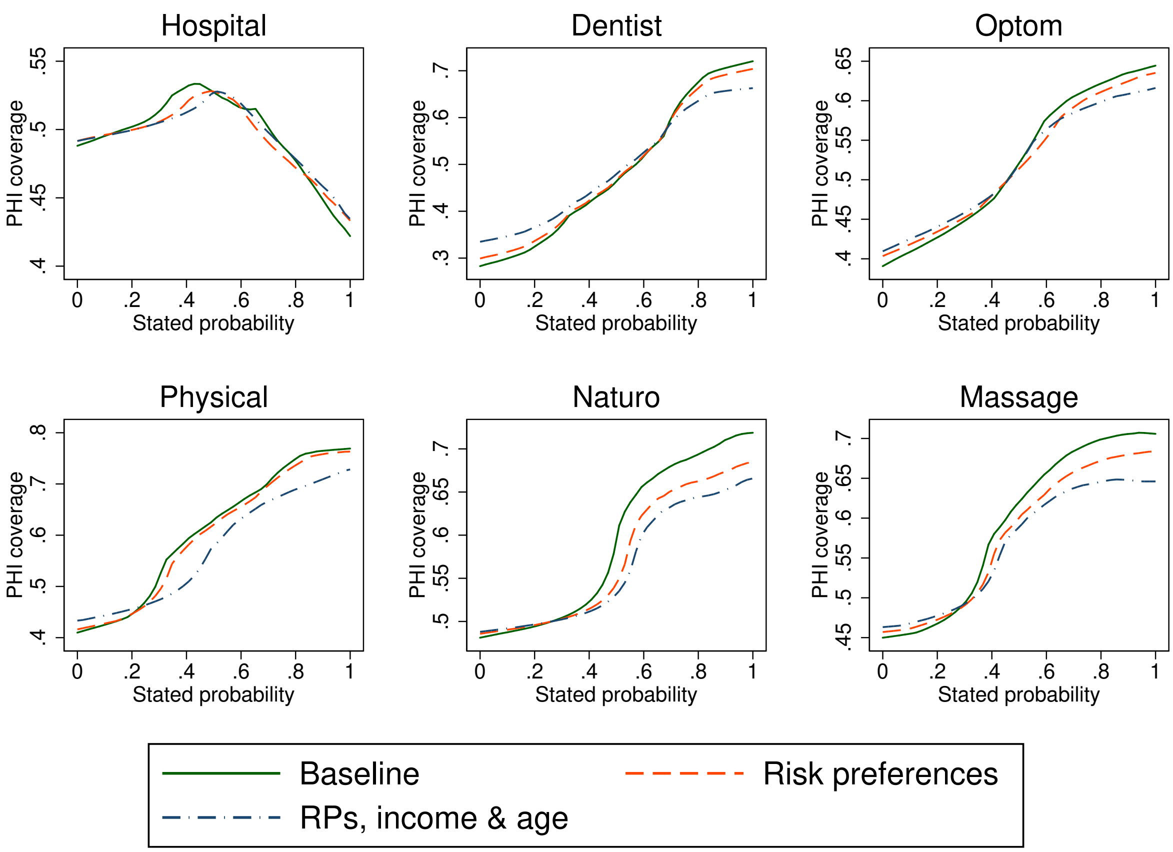
Figure C1: Distribution plots (frequencies): risk preferences



to the residuals from these estimations, and the local polynomial fits are compared to the baselines without controls (see Figures C2 and C3).

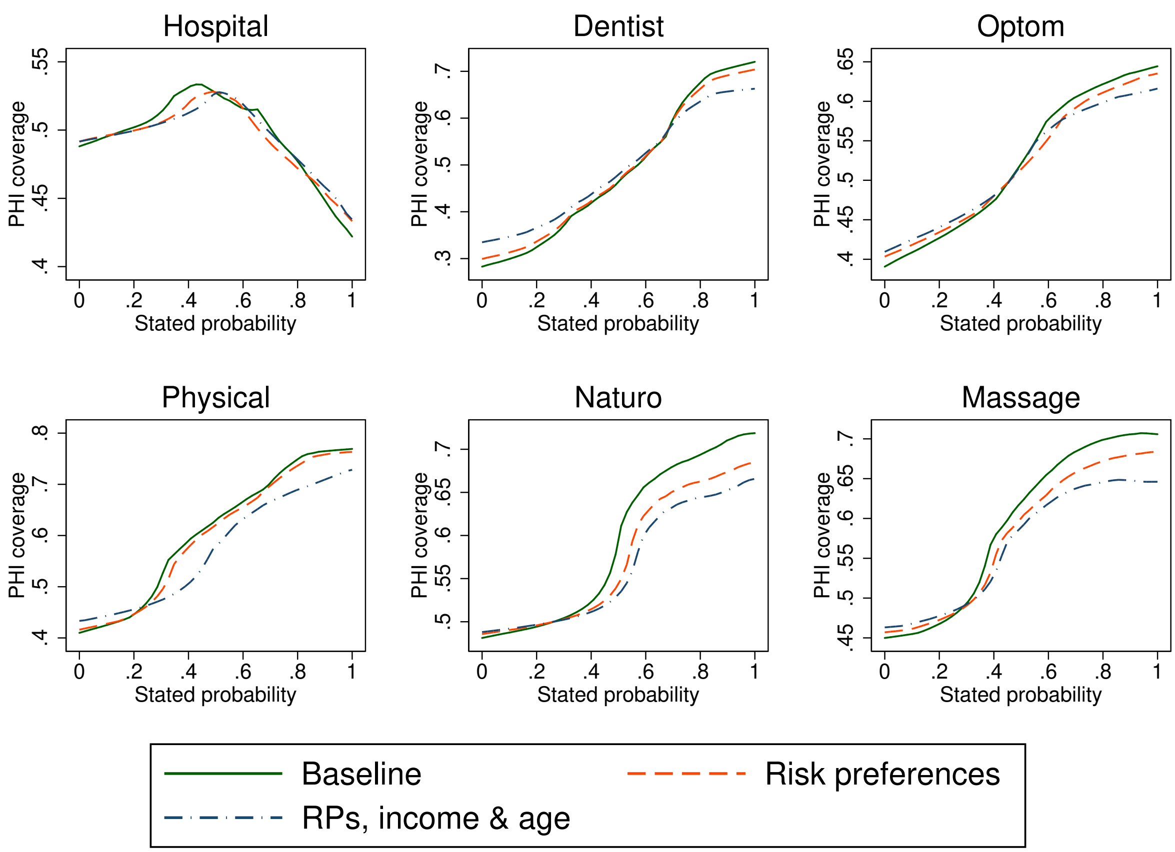
It is important to recognize that difference between the residualized fits and the baseline are not necessarily attributable to the policy incentives. Age, income and family status may mediate the relationship between risk and insurance for reasons other than government policy. I first control only for risk preferences, and then also include controls for age, income and family status. Controlling for risk preferences has little effect on the correlations. The additional controls also have a limited effect. Overall, the correlations are not greatly affected by these factors.

Figure C2: Correlations between subjective expectations and private health insurance



Note: For Hospital, private health insurance coverage is a dummy for any type of private health insurance policy that includes hospital cover. For other health services, coverage is any type of policy that includes ancillaries cover. Line fits are based on local polynomial smoothing regressions estimated using Stata 14 (Epanechnikov kernel, 50 cut points and rule-of-thumb bandwidth). Baseline: no controls; Risk preferences: residualized PHI coverage after controlling for stated and hypothetical risk preferences; RPs, income and age: residualized PHI coverage after controlling for risk preferences, income, age (quadratic), couple status and couple status interacted with income. n=1,528.

Figure C3: Correlations between subjective expectations and private health insurance: Childless singles



Note: See Figure C2. n=482.

D Additional details from structural estimation

In this appendix I provide additional details on the structural estimation in Section 4.3.3.

D.1 Notes on estimation

Note that the probability function in Eq. 5 can be recast as below, with $P_{i,j}$ denoting the probability for individual i of choosing option j (private insurance or no private insurance):

$$P_{i,j} = \frac{\exp(EU_{i,j})}{\exp(EU_{i,phi=1}) + \exp(EU_{i,phi=0})}. \tag{D1}$$

The log-likelihood is then

$$\ln L = \Sigma_{i \in N}(\Sigma_{j \in \{phi=0,phi=1\}} P_{i,j}.\mathbf{1}.\mathbf{D_i},\mathbf{j}) \tag{D2}$$

where $\mathbf{1}.\mathbf{D_i},\mathbf{j}$ is an indicator for if j equals the actual choice made. This setup is equivalent to the setup presented in Section 4.3.3, but is more complicated. For estimation, it requires expanding the dataset so that there are $N \times J$ observations. Nevertheless, I obtained estimates by maximizing Eq. D2 rather than Eq. 6 because I found that the estimates reached convergence more reliably.

The γ^k's were estimated as $\exp(\gamma^k)$ to ensure the correct sign. The estimation also imposes the restriction $\gamma^H \leq \gamma^{S|Q^{PR}}$ and $\gamma^H \leq \gamma^{S|Q^{PU}}$ by estimating $\gamma^{S|Q^{PR}}$ as $\gamma^H + \tilde{\gamma}^{S|Q^{PR}}$ and $\gamma^H + \tilde{\gamma}^{S|Q^{PU}}$. However, I do not impose the restriction that $\gamma^{S|Q^{PR}} \leq \gamma^{S|Q^{PU}}$, which allows people to prefer public to private hospital care.

D.2 Calculating welfare

The utility is equalized between the good and bad health state when

$$\frac{Y_i^{1-\gamma^H} - 1}{1-\gamma^H} = \frac{\tilde{Y}_i^{1-\gamma^{S|Q^k}} - 1}{1-\gamma^{S|Q^k}}. \tag{D3}$$

Solving for $\tilde{Y}_i$

$$\tilde{Y}_i = \left[\frac{Y_i^{1-\gamma^H} - 1}{1-\gamma^H}.(1-\gamma^{S|Q^k}) + 1\right]^{\frac{1}{1-\gamma^{S|Q^k}}}. \tag{D4}$$

$\tilde{Y}_i - Y_i$ then gives the compensation needed to make person i indifferent between being in the good health state, and being in the bad health state and receiving k quality care. For example, when $\gamma^{S|Q^k} = \gamma^{S|Q^{PR}}$, this corresponds to $Y'' - Y'$ in Figure 10.

D.3 Estimation results

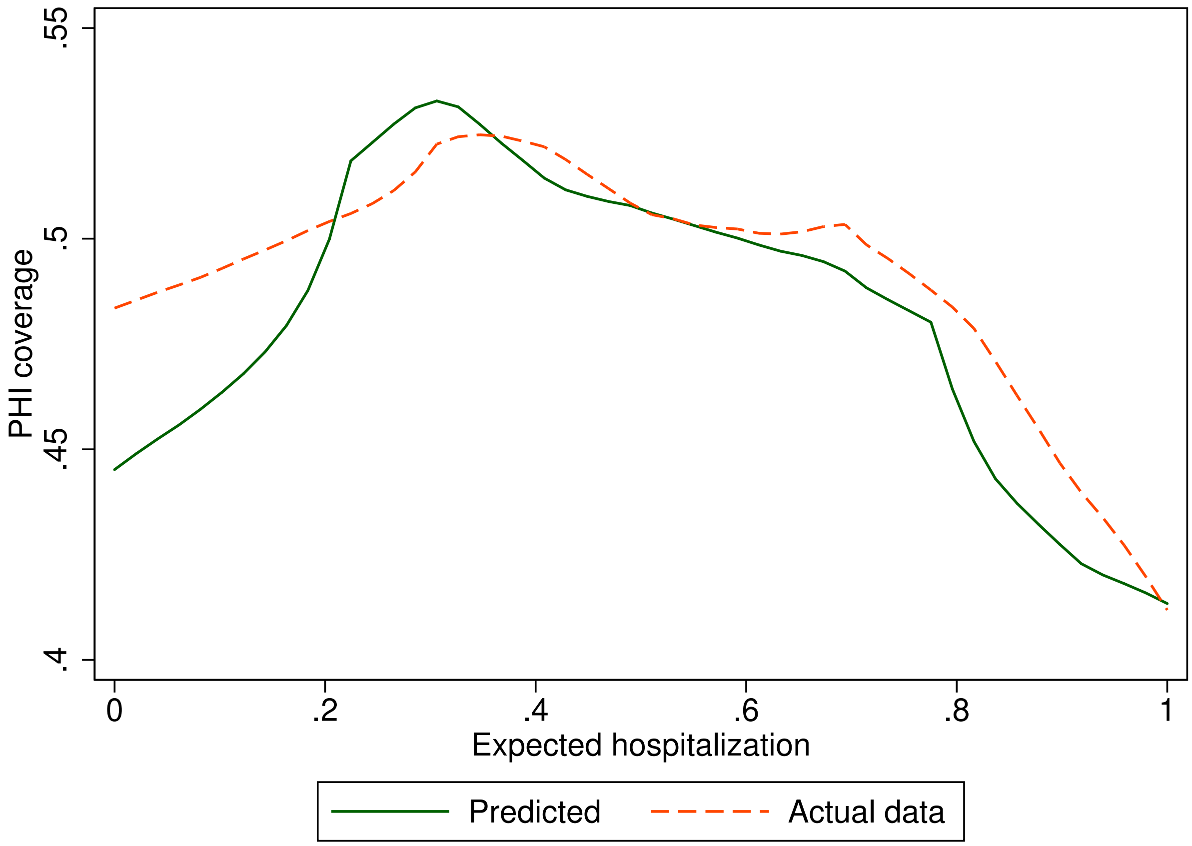
Table D1: Structural equation estimates for insurance choice

	$\exp(\gamma^H)$		
Prob. hospitalization			-1.253
			(1.073)
Prob. hospitalization^2			0.902
			(3.355)
Prob. hospitalization^3			1.020
			(2.716)
Risk pref.			-0.117
			(0.100)
Age			0.000
			(0.004)
Male			-0.146
			(0.105)
City			-0.106
			(0.125)
Edu Degree			0.475
			(0.318)
Couple			0.053
			(0.079)
Constant	-0.537***	-0.589***	-0.256
	(0.051)	(0.051)	(0.446)
	$\exp(\tilde{\gamma}^{S\|PR})$		
Prob. hospitalization			10.531
			(7.750)
Prob. hospitalization^2			-23.309
			(18.115)
Prob. hospitalization^3			14.186
			(11.936)
Risk pref.			-0.620*
			(0.339)
Age			0.044
			(0.031)
Male			-3.306
			(2.586)
City			-2.855
			(2.302)
Edu Degree			0.157
			(1.336)
Couple			-0.493
			(0.781)
Constant	-23.359***	-18.131***	0.022

	(1.296)	(0.470)	(2.206)
	$\exp(\tilde{\gamma}^{S\|PU})$		
Prob. hospitalization			10.731
			(6.746)
Prob. hospitalization^2			-20.223
			(14.580)
Prob. hospitalization^3			9.488
			(9.096)
Risk pref.			-0.641**
			(0.261)
Age			0.057**
			(0.029)
Male			-2.007***
			(0.484)
City			-1.180
			(0.844)
Edu Degree			2.302
			(1.540)
Couple			0.285
			(0.379)
Constant	-5.217***	-4.991***	-2.038
	(0.213)	(0.178)	(1.570)
$\exp(s)$		-0.616***	-1.463***
		(0.080)	(0.353)
Observations	2794	2794	2794

Note: Prob. hospitalization is the person's subjective probability of visiting a hospital in the next 12 months. Risk. pref. is a the person's stated willingness to take financial risks [1-4 scale], as described in Appendix C. Couple refers to those in either registered marriages or de-facto relationships. Other controls are defined in Table A1. Cluster-robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure D1: Comparison: stated expectations vs predicted expectations and PHI coverage



Note: Private health insurance coverage is a dummy for any type of private health insurance policy that includes hospital cover. Line fits are based on local polynomial smoothing regressions estimated using Stata 14 (Epanechnikov kernel, 50 cut points and rule-of-thumb bandwidth). n=1,528.