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Waiting times and the decision to buy private health insurance

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Project team

Dr Meliyanni Johar[1]
A/Prof. Glenn Jones[2]
Prof. Michael Keane[1]
A/Prof. Elizabeth Savage[1]
Ms Olena Stavrunova[1]

1. University of Technology, Sydney
2. Macquarie University

Contact details

Dr Meliyanni Johar
Centre for Health Economics Research and Evaluation (CHERE)
University of Technology, Sydney
City Campus
PO Box 123 Broadway
NSW 2007

Tel: + 61 2 9514 4720
Fax: + 61 2 9514 4730
Email: meliyanni.johar@chere.uts.edu.au

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Abstract

Over 45% of Australians buy health insurance for private treatment in hospital. This is despite having access to universal and free public hospital treatment. Anecdotal evidence suggests that one possible explanation for the high rate of insurance coverage is to avoid long waiting times for public hospital treatment. In this study, we investigate the effect of expected waiting time on individual decisions to buy private health insurance. Individuals are assumed to form an expectation of their own waiting time as a function of their demographics and health status. We estimate models of expected waiting time using administrative data on the population hospitalised for elective procedures in public hospitals in 2004-05 and use the parameter estimates to impute expected waiting times for individuals in a representative sample of the population. We model the impact of expected waiting time on the decision to purchase private health insurance. In the insurance demand model, cross-sample predictions are adjusted by the individuals' probability of hospital admission. We find that expected waiting time does not increase the probability of buying insurance but a high probability of experiencing a long wait does. Overall we find there is no significant impact of waiting time on insurance purchase. In addition, we find that the inclusion of individual waiting time variables removes the evidence for favourable selection into private insurance, as measured by self-assessed health. This result suggests that a source of the favourable selection by reported health status may be aversion to long waits among healthier people.

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1 Introduction

In tax-financed health care systems, where the price of health care is essentially zero and budgets for publicly-financed health care are capped, explicit waiting lists are the most common means of rationing demand. Australia, New Zealand, the UK, Canada and Scandinavian countries use waiting lists to allocate non-emergency health treatments at public hospitals. Waiting lists for elective surgery serve as a health care allocation mechanism which equilibrates supply and demand in the absence of prices. Australians have access to universal and free public hospital treatments but 45% of the population choose to buy health insurance for private hospital treatment. This is despite paying significant insurance premiums and facing potentially large out-of-pocket expenditures when treated as a private patient. Anecdotal evidence suggests that duplicate public and private coverage is partially driven by long waiting lists and waiting times for the free public hospital treatments. Another advantage of having private health insurance in Australia is that it gives private patients choice over the settings of care. For example, private patients can choose to be treated in private hospitals, nominate their own doctors, and have private accommodation. There are also financial incentives to insure, comprising both a subsidy to premiums and a tax on the high-income uninsured.

In this paper, we investigate how an individual's expected waiting time for elective surgery in public hospitals influences their decision to buy private health insurance. As waiting is costly (e.g., Besley *et al*., 1999; Johannesson *et al*., 1998), waiting times are potentially a major factor driving individuals' decision to buy health insurance. To our knowledge, this is the first study that explores this relationship at the individual level, modelling individuals' expected waiting times as a function of their own demographics and chronic conditions. Furthermore, the data available are very detailed, involving over a hundred different categories of chronic conditions.

To empirically test the relationship between waiting time and insurance purchase, we need data on both insurance and waiting time. However, no single large data set in Australia contains both of these variables: household surveys provide information about insurance status but have no waiting information, while waiting time administrative records from hospitals contain unreliable information on health insurance. To overcome this difficulty, the analysis combines information from three data sets. First, the National Health Survey (NHS) 2004-2005 is used to provide data on insurance, health conditions, lifestyle factors, income and socio-demographics. This is the main data set from which the insurance equation will be estimated. Second, linked Inpatient and Waiting Times (IWT) data for elective surgery admission to public hospitals in New South Wales (NSW) in 2004-2005 is used to estimate waiting times for different demographic groups and regions and for various health conditions. The parameter estimates based on the IWT data are used to impute mean waiting time and probability of a long wait for each NHS observation taking into account the probability of a hospital admission. Third, the Household Expenditure Survey 2003-2004 is used to construct expected premiums associated with insurance purchase for each NHS observations.

We estimate a series of insurance demand models, where insurance status is assumed to be a function of expected waiting time and the probability of a long wait. We also investigate how the independent effects of variables commonly found to influence insurance demand (e.g., Savage and Wright, 2003; Ellis and Savage, 2008; Fiebig et al., 2006) are affected by the inclusion of expected waiting times measures. For example, high-income individuals may value time more highly, and buy insurance to avoid waiting. If so, significant income effects on insurance purchase found in previous studies may be picking up the effects of expected waiting time that is absent in these models. Similarly, the positive relationship between self assessed health status and insurance demand in Australia (e.g., Doiron et al., 2008; Buchmueller et al., 2008) may be due to the omission of waiting times in models of insurance demand.

2 Literature

Waiting for health care is costly for individuals because a good is worth less today if its consumption is delayed (Lindsay and Feigenbaum, 1984), and also because delay in medical treatment may prolong suffering, decrease earning capacity and cause deterioration of quality of life in general for the duration of wait. For example, Leung et al. (2004) find that patients who value time highly tend to choose private treatment that is readily accessible and are prepared to pay to reduce waiting time to treatment. Propper (1990; 1995) and Johannesson et al. (1998) also find evidence that individuals are willing to pay to avoid waiting for medical treatment. They find that willingness to pay is non-trivial on average, and varies with income and other socio-economic characteristics. Some individuals will prefer to opt out of free public sector treatments to avoid waiting times even if the private alternative involves out-of-pocket payments to the providers of care. Many such individuals will purchase private health insurance to smooth their health care spending.

Besley et al. (1999) estimate an insurance demand model using repeated cross-section data on individuals in the UK. By utilising regional variations public hospitals' waiting lists, they find that the size of waiting list increases the probability of individuals buying insurance. Jofre-Bonet (2000) reaches similar conclusion using data from Spain.

When waiting time data is not available, studies have used some measure of perceived quality of public hospital (Costa-Font and Font-Vilalta, 2004; Costa and Garcia, 2003; Johannesson et al., 1998). Costa and Garcia (2003) use expressed satisfaction with the public system as an indicator of quality. They find that perceived lower quality of the public sector increases the probability of purchasing private insurance in Catalonia. In Ireland, where the relationship between public and private health care and private insurance shares many similarities with Australia, Harmon and Nolan (2001) find that perceptions about the waiting times for public hospital treatment have been a factor in the growth of insurance coverage. Asking some 1,100 insurees on reasons for having health insurance, 86% nominate '[b]eing sure of getting into hospital quickly when you need treatment' as very important. In addition, they ask these respondents to rank 8 of the listed reasons for having health insurance, ranging from monetary concern to ability to obtain exclusive treatment, 77% rank the accessibility factor as the most important factor. Colombo and Tapay (2004) write "[i]ndeed, the main reason why individuals buy private cover is to ensure quick access to care" [p.43].

Related literature consists of experimental studies finding that private patient status allows timely access to health treatment. Lungen et al. (2008) find some evidence that physicians treat patients differently in the waiting list according to their insurance status. In Germany, physicians receive 20%–35% higher reimbursement for patients with private health insurance than those with statutory insurance. This study recruits callers and assigns them randomly to two groups, one with private insurance and the other with statutory insurance. They then call private specialist practices and make appointments. Callers with statutory insurance have to wait 3 times longer for an appointment than callers with private insurance. In the US, studies have also found that the privately insured are ahead of their uninsured counterpart in the appointment process (Asplin *et al*., 2005; Wang *et al*, 2004).

3 Theoretical background

To provide theoretical motivation for insurance purchase, we follow the seminal work by Besley et al. (1999). Consumers are utility-maximisers who face some probability of falling ill. The treatment options available are either public health care, which is free but may involve waiting, or, they can go "private". Private treatments can be performed at private hospitals or public hospitals with private patient status. We assume that private patients are insured.

They face some positive price but avoid waiting. Utility-maximising consumers buy insurance if their expected utility from being insured is greater than that of remaining uninsured. The greater is the inflexibility manifested in the public system, the greater would be the gain from buying private insurance. Long waiting times in public hospitals is one form of inflexibility in the public system.[1]

Let the probability of falling ill be $\alpha \in [0,1]$, and the utility of an individual in the good health and bad health state be $U(y)$ and $u(y)$, respectively, where y denotes income. The difference in the utility functions allows for higher marginal utility of income in the good health state (Viscusi and Evans, 1990). Assume that $U_y > 0$, $U_{yy} < 0$, $u_y > 0$ and $u_{yy} < 0$. Assume that falling ill requires non-emergency treatment, for which demand in public hospitals is controlled by a waiting list and that private treatment involves zero waiting time. Also assume that if treatment is delayed by w days, the individual's utility in a bad health state is discounted by the function $g(w)$ where $g(0) = 1$ and $0 \leq g(w) \leq 1$, and $g(w + \Delta) - g(w) \leq 0$, so that the total utility of an individual who falls ill and spends w days on a public hospital waiting list before being treated is given by $u(y)g(w)$ (see Martin and Smith 1999).

Waiting time w is ex-ante unknown, but individuals know its distribution $F(w)$ conditional on their own health status and demographics, so they can form an expectation, $E(g(w)) = \int_0^\infty g(w)F'(w)dw$ given their characteristics. Similarly, they use the knowledge of their own health conditions and demographics to form an ex-ante expectation of their probability of hospital admission, α. A market for health insurance sells contracts at an equilibrium fair premium π (i.e., the expected costs of private healthcare). In the case of full insurance, insured individuals will always choose private hospital treatment. However, if only partial coverage is available, insurees incur some out-of-pocket costs for private treatment. Let *l* be the net expenditure after insurance reimbursement. The expected utility of an individual without and with insurance then can be written as

(1) $$EU^0 = \alpha u(y)E(g(w)) + (1-\alpha)U(y)$$

(2) $$EU^1 = \alpha u(y - \pi - l) + (1-\alpha)U(y-\pi)$$

[1] Another inflexibility of public health care is that patients cannot choose their doctor.

respectively, where α and w are assumed to be independent, conditional on individual health conditions and demographics. With insurance, income is reduced by the insurance premium in either state. An individual will buy insurance if

(3) $$EU^1(\alpha,\pi,l,y) \geq EU^0(\alpha,E(g(w)),y)$$

The gain in expected utility from buying insurance is greater the larger is the expected discounting effect of waiting times $E(g(w))$, the lower is the insurance premium π, and the smaller is l. For a given functional form of $g(w)$, the magnitude of $E(g(w))$ will depend on $F(w)$, so in the empirical application we approximate $E(g(w))$ by the features of the distribution of waiting times conditional on health status and demographics distribution. We choose two measures which are likely to be important determinants of $E(g(w))$: the expected waiting time and the probability that waiting time exceeds some value towards the upper tail of the distribution.

We have simplified the model by neglecting the presence of individuals who prefer longer to shorter waiting times (Cullis and Jones, 1986; Johannesson et al., 1998), and individuals who are captive to the public system (Costa-Font and Font-Vilalta, 2004).

4 Empirical strategy

4.1 Data

Our data augmentation strategy follows Fang *et al*. (2008). The three data sets we use are: (i) the National Health Survey (NHS) 2004-2005; (ii) the NSW Inpatient and Waiting Times (IWT) data 2004-2005; and (iii) the Household Expenditure Survey (HES) 2003-2004. We focus on NHS households that reside in NSW, as the IWT data is based on NSW public hospital admissions. The information from the IWT and NHS data can be written as

(4) $$\begin{cases} [w_i, H_i, Z_i]_{i \in K_{IWT}} \\ [I_j, H_j, Z_j, \alpha_j, \mathrm{M}_j, \mathrm{Y}_j, X_j]_{j \in K_{NHS}} \end{cases}$$

where K_{IWT} and K_{NHS} are indicator variables for IWT and NHS samples, respectively. The observation unit is an adult aged over 18 years.

In (4) w_i denotes waiting time, as measured by the number of days between the listing and admission (removal) dates that appear only in the IWT data. The variables $\{H, Z\}$ denote chronic conditions and demographics (age and sex and their interactions, and geographic locations) that are common in both data sets. They are assumed to determine individual expectations of waiting times. There are over 10,000 ICD10AM codes for physician's diagnoses in the IWT data. These codes are much more detailed than the 108 long term condition codes used in the NHS data. We obtained clinical advice to first map the ICD codes to the NHS codes and then to aggregate these NHS codes to 25 groups of chronic conditions clinically relevant to hospital admission, H. For example, the group of 'eye diseases' relevant to hospitalisation include cataract, glaucoma, and macular degeneration but not glasses.

I_j is an indicator variable for insurance choice in the NHS data, Y_j captures variations in economic status of individuals (income and education), M_j includes lifestyle variables such as measured by smoking status, exercise schedule, alcohol consumption and body weight, and use of glasses, and X_j includes other relevant variables available in the NHS data such as age, family unit type (e.g., single household, couple with or without dependant), foreign born, region and self-assessed health. These variables have been found to influence selection into the insurance market (Fang *et al*., 2008; Buchmueller *et al.*, 2008; King and Mossialos, 2005), and variations in the cost of waiting across individuals (Costa-Font and Font-Vilalta, 2004). Finally, α_j is an indicator variable for hospital admission[2] which will be subsequently used to estimate an individual probability of hospital admission to be utilized in the construction of waiting times variables.

Our empirical model of insurance demand takes the form

$$(5) \qquad \begin{cases} \hat{W}^* = f(H, D) \\ I = \hat{W}^* \varphi_1 + D\varphi_2 + P\varphi_3 + \eta \end{cases}$$

where $\hat{W}^*$ is the vector of waiting times variables, including expectation of waiting time and probability of extremely long wait, both multiplied by the probability of requiring a hospital admission. The model is estimated using information on individuals in the NHS. The expected waiting time and probability of extremely long wait are imputed for individuals in NHS using prediction models which relate waiting times and incidence of long waits to health conditions *H* and demographic characteristics *D,* and are estimated with IWT data. The probability of hospital admission is predicted from a model which relates incidence of hospital admission to H and D in the NHS data. These prediction models will be discussed in detail in the following sections.

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[2] The NHS data is representative of the general population, not everyone in this sample experiences a hospital episode.

The three sets of explanatory variables are the following: *D* variables affect both health, and hence waiting, and insurance demand (age, gender, lifestyle, region, foreign born); *P* variables affect insurance choice alone (income, education, premium, family structure). The *H* variables are measures of health (health conditions, number of conditions and self reported health) that consumers use to predict the likelihood of hospital admission and expected waiting time conditional on admission.

We assume that the *H* variables do not affect the demand for insurance directly, but only through their affect on expected waiting time. In our view this makes intuitive sense: in a system with free public hospital cover, being less healthy should not increase the demand for private insurance *per se*. It should only affect demand to the extent that ones' health conditions are such that one is more likely to experience an incidence of illness/disease that would entail a long wait for treatment. However, we will test this hypothesis by including self reported health in the insurance demand equation directly and seeing if it has an independent effect from expected wait on insurance demand.

4.2 Imputation of waiting times variables

In the IWT sample, we focus on Medicare-eligible public patients who are on the public hospital waiting list for elective surgery. They make up more than 80% of the total hospitalised population for elective surgeries in public hospitals. The IWT sample consists of 175,218 observations, so the estimates are likely to be close to the hospitalised population's true parameters.

To allow for co-morbidities, where some diseases more are likely to occur together than others and these interactions are likely to impact on the severity of health state, we use factor analysis on the set of 25 health conditions, *H*. We retain 12 factors, *F*, with eigenvalues larger than one. The factor weights are used to generate corresponding factors for the NHS sample. Table I reports the factor loadings. The factor loadings indicate common patterns of co-morbidities. For example, IWT factor 1 has high loadings on several potentially serious conditions, IWT factor 3 focuses on bone diseases and IWT factor 4 loads highly on metabolic and mental disorders.

Table I

Summary statistics of waiting time and demographics for the IWT sample are presented in Table II. The mean waiting time is 97 days, but 10% of patients wait longer than 291 days.

There are slightly more females in the sample than males and almost 70% of patients have more than one condition. This highlights the importance of using health factors in the linear prediction of waiting time, instead of treating diseases as independent.

Table II

The prediction model for expected waiting days is given by

(6) $w_i = \theta_0 + \theta_1 H_i + \theta_2 D_i + \varepsilon_i$

which is estimated by Ordinary Least Square (OLS).[3]

We define a long wait as having an actual wait in the top 10% of the waiting time distribution. Both anecdotal and aggregate-level evidence (Besley *et al.*, 1999) suggest that people buy insurance due to concern about long waits. Thus, we expect individuals with high probability of experiencing a long wait to have a higher probability of buying private health insurance. The prediction model for the probability of long waits $\Pr\left(wait_i > 291 \text{ days} \mid H_i, D_i\right)$ is the linear probability model:

(7) $lw_i = \delta_0 + \delta_1 H_i + \delta_2 D_i + \nu_i$,

where lw_i is an indicator that waiting time of individual *i* exceeds 291 days in IWT.[4]

Table III presents the results for Equations (6) and (7). All health factors, except factors 1 and 9, are significant in both models. The largest positive impact on waiting is from factor 3, which represents individuals with bone conditions and fractures and alcohol and drug-related conditions (12 days longer wait and an increase in probability of a long wait of 0.02). Factors

[3] We maintain the natural scale of the waiting time series despite positive skewness to avoid retransformation problems. A smearing correction that assumes homoskedastic variance will only rescale the predicted values when we cross-predict to the NHS data, whilst a smearing correction that adjusts for heteroskedasticity would either require an assumption about the form of the heteroskedasticity or involve some auxiliary regressions of the squared residuals to estimate the unknown form of the heteroskedasticity. Comparing the predicted values from the non-transformed model and a log model retransformed using heteroskedastic smearing factor with an unknown form of heteroskedasticity, we find that predictions from the former exhibit higher correlation with the actual series. Furthermore, the linear transformation of the log model is not mean-preserving. Alternative models to OLS were also estimated including a generalised linear model with a log link function and finite mixture models, and it was found that OLS performed no worse, if not best, in terms of predictive power than these competing models. We also tested for interactions with region and number of conditions but they did not contribute to the explanatory power of the model.

[4] Because the IWT sample contains no data on self assessed health, the *H* vector contains chronic conditions and number of conditions. Self assessed health enters $\hat{W}$ through the probability of admission.

8, 10 and 11 generate somewhat longer waits; these load heavily on respiratory and metabolic conditions (factor 8), osteoporosis (factor 10) and varicose veins and other vein diseases (factor 11). The largest negative impact on wait (over 30 days shorter and a lower probability of a long of 0.06) is from factor 4; this has high positive loadings on mental and stomach conditions and a large negative loading on eye conditions. The latter is a reflection of long waiting times for cataract surgeries (over 6 months) compared with other elective procedures. Factor 6 lowers expected wait by about 16 days and has a high positive loading on diseases of female pelvic organs and genital tract.

With regard to demographics, there is a positive age gradient, with those aged less than 40 waiting less compared with those aged 40-45 and those age 60 or more waiting longer (except for those aged over 84). The longer waits for those over 60 are significantly greater for females. There is a strong positive gradient on the number of conditions: those with 5 or more conditions wait on average 25 days longer than those with 1 condition. This positive gradient is likely to represent complexity, as the gradient on conditions is reversed when diseases enter the model as independent variables, instead of as factors. Lastly, expected wait for patients living in major cities and inner regional areas are longer than those who live in outer regional areas. This result may be explained by variations in supply conditions, such as available beds. Having multiple conditions also increases the probability of long wait. Patients in major city and inner regional areas are more likely to experience a long wait than outer regional residents.

Table III

Figure 1 indicates how well the mean waiting time predictions fit the waiting time data. It ranks observations by predicted wait and plots the average predicted wait (X-axis) against the data mean wait (Y-axis) for every 5th percentile of the predicted values. The figure shows that the predictions fit the data well, but underestimate slightly in the tails of the distribution.

Figure 1

We use the estimated Equations (6) and (7) to impute the expected waiting time and the probability of a long wait for each person in the NHS sample. The NHS sample comprises 3,989 observations. The imputed variables are:

$$(8) \quad \begin{aligned} E(w_j) &= \hat{w}_j = \hat{\theta}_0 + \hat{\theta}_1 X_j + \hat{\theta}_2 Z_j \\ E(lw_j) &= \hat{l}w_j = \hat{\delta}_0 + \hat{\delta}_1 X_j + \hat{\delta}_2 Z_j \end{aligned}.$$

In the cross-sample predictions, no predicted waiting times are negative and none of the predicted probabilities of a long wait lie outside the unit interval.

The expected waiting times and probability of long wait must be adjusted by the probability of requiring hospital admission. It is possible that an individual who is likely to face a long waiting time once she requires hospital treatment has a very low likelihood of needing the treatment. Such an individual would not try to insure against a long wait because her chances of actually experiencing it are very small. Hence, the effect of waiting times depends on the probability of requiring hospital admission. To account for this in the insurance demand model we multiply the predicted *conditional* waiting times variables from equations (8) by the probability of hospital admission, which is estimated using data on incidence of hospital admission of individuals in NHS.

4.3 Admission probabilities and insurance premiums

About 18% of the NHS sample had a hospital episode in the last 12 months. Just as co-morbidities matter to waiting time, so they affect probability of admission. For this reason, we conduct factor analysis on the NHS sample using the 25 health conditions. Table IV presents the NHS factor weights. Factor 1 is a 'bad health' factor which loads highly on many serious conditions. Factors 2, 3 and 5 load highly on several conditions.

Table IV

Table V presents the summary statistics of the NHS data used to model admission. Hospital admission for an individual is modelled using a probit specification as:

(9) $$A_j^* = \phi_0 + \phi_1 H_j + \phi_2 D_j + \psi_j \qquad \begin{cases} A_j = 1 \text{ if } A_j^* > 0 \\ A_j = 0 \text{ otherwise} \end{cases}$$

where A_j^* is a continuous and latent variable measuring the net benefits of hospital admission, A_j is the observed admission status, X_j include demographics, lifestyle variables and region and X_j includes NHS factors and self assessed health. We assume ψ_j to be normally distributed and estimate the coefficients using a probit regression. We denote individual probability predictions from the model as $\hat{\alpha}_j$.

Table VI presents the results for hospital admission model. The bad health factor, NHS factor1, has a significant and positive effect on admission probability. Factors 2, 3 and 5 are also associated with higher probability of admission but to a lesser extent. Factor 2 has large loadings on mental health, alcohol and drug-related conditions, epilepsy and migraine. The highest loading for factor 3 is on diseases of male organs and factor 5 loads heavily on fractures and congenital abnormalities. Age, weight, smoking and exercise, and location have low predictive power on hospital admission. The foreign born are less likely to be admitted, while non-drinkers are more likely to be admitted than drinkers.

Tables V and VI

We next calculate an "effective" health insurance premium for each observation. Neither the IWT nor NHS samples contain data on premiums. We construct a premium variable using available information on age, income, and income unit type in the NHS data. Due to the community rating system in the Australian market for private health insurance, insurers cannot price discriminate based on individuals' observable risk factors, such as age and past claims. For a given contract, price varies according to whether the insurance contract covers a single person, a sole parent, or a couple (with or without dependants). For each individual j we construct the expected premium associated with insurance purchase based on a standard hospital cover policy. To calculate the "effective" premium, $\hat{\pi}_j$, adjustments are made to the standard premium to reflect the impact of several government policies. First, the Lifetime Health Cover adds 2% to the price for each year individual j was uninsured since his/her 30th birthday. The age surcharge is capped at 70%. Second, there is a government rebate of 30% (in 2004-2005). Finally, the premium is adjusted by the Medicare Levy Surcharge (MLS) of 1% taxable annual income for those not having private health insurance. The levy surcharge is applicable to singles earning over $50,000 and couples earning more than $100,000, with each child after the first in the family increasing the threshold by $1,500.

The use of the third data source, HES, is related to this last adjustment. In particular, we need to construct a household gross income series. In the NHS, the income variable is top-coded and adjusted by household composition. For each equivalised income decile and household composition combination, we find the corresponding household non-equivalised income using the HES sample. The MLS has an important implication for the private health insurance market because it can attract high-income earners into the market to avoid a high levy surcharge which over certain income levels can exceed the cost of the standard premium.

4.4 Insurance purchase and expected waiting time

The augmented NHS data then can be written as:

(10) $\left\{I_j, \hat{\alpha}_j, \hat{w}_j, l\hat{w}_j, \hat{\pi}_j, P_j, D_j, S_j\right\}_{j\in K_{NHS}}$,

where I_j indicates insurance status, $\hat{\alpha}_j$ is predicted probability of admission, $\hat{w}_j$ and $l\hat{w}_j$ are predicted mean wait and predicted probability of a long wait, $\hat{\pi}_j$ denotes insurance premium and Medicare levy status , P_j are income and education variables, D_j are demographics, region and lifestyle variables, and S_j are self assessed health status. Here we separate S_j, from D_j. Recall that we hypothesize that *S* should not affect *I* directly but only through its effect on expected waiting times. But in some specifications we include it to test this hypothesis. Conversely, we also want to test if the “advantageous” selection pattern (i.e., people with better SAH tend to buy more insurance) is an artefact of excluding expected from the insurance demand equation.

We use factor analysis on the lifestyle variables (exercise, body mass, smoking and alcohol consumption) to allow for interactions and derive ‘types’ of individuals distinguished by their lifestyles. Table VII presents the lifestyle factor loadings for the 5 factors. LFactor 1 has loadings consistent with an ‘average’ type of person: overweight but not obese, moderate exercise and drinking, and low smoking. LFactor 2 we term ‘bad’: obese, heavy smokers and heavy drinkers. LFactor 3 types, termed ‘lazy’, are sedentary smokers who don’t drink and don’t reveal their weight. In contrast LFactor 4 are ‘aspirational’ types who exercise, drink a bit but don’t smoke, and conceal their weight but are not thin. LFactor 5 types, the ‘driven’, are extreme exercisers who are underweight, do not smoke or drink and don’t wear glasses.

Table VII

Table VIII presents variable means by insurance status. The mean predicted waits and the probability of a long wait are almost equal for the insured and uninsured, however the uninsured are more likely to be admitted to hospital. The characteristics of the insured sample are not surprising: relative to the uninsured sample, they tend to be born in Australia, richer, highly educated, are not in the retirement pool and live in the city. Overall the MLS exceeds the insurance premium for 8.8% of individuals in the sample; most of them are high income earners (in the 9th and 10th deciles of the income distribution) or couples with dependent(s). For these observations, we set their premium to zero and flag this with a dummy variable. The proportion of the insured sample facing the MLS is over 4 times that of the uninsured.

Table VIII

The insurance demand model can be written as:

(9) $$I_j^* = \phi_0 + \phi_1(\hat{\alpha}_j \cdot \hat{w}_j) + \phi_2(\hat{\alpha}_j \cdot l\hat{w}_j) + \phi_3\hat{\pi}_j + \phi_4 P_j + \phi_5 D_j + \phi_6 S_j + \vartheta_j$$

where I^* is the latent utility from having insurance and $I = 1$ if $I^* > 0$, and ϑ is the random component of the insurance demand.

Table IX presents a series of regression results for linear probability models of insurance demand. Model 1 has no expected wait variables but includes all other controls, including self assessed health. Model 2 includes mean predicted wait and predicted probability of a long wait and all controls except for self assessed health. Model 3 tests for an independent effect of self assessed health once waiting variables are included.

Table IX

In model 1 there is a strong gradient on self assessed health: those with worse self reported health are significantly less likely to purchase insurance. This result is consistent with much of the literature which finds that the insured are a favourable selection of the population.[5] However, after the inclusion of waiting time variables (model 3), the effects of self assessed health on insurance demand are substantially reduced, especially for poor health, and no longer significant at the 5% significance level.

This result supports the hypothesis that self assessed health affects insurance demand through its effect on health-related concerns, which include waiting time, and has no independent effect on insurance demand. The favourable selection commonly found in insurance demand models may be partly due to failing to control for the effect of waiting time. In particular, because waiting time is negatively related to both insurance and health, omitting it from the model results in negative bias in the effect of bad health on insurance demand.

[5] This has been reported previously (see Propper, 1989; Hurd and McGarry, 1997; Shmueli, 2001; Cardon and Hendel, 2001; Asinski, 2005; Fang *et al.*, 2008; Doiron *et al.*, 2008; Buchmueller *et al.,* 2008).

Across all models, the impacts of other controls are stable. Higher income and education increase insurance demand, consistent with the usual findings. Single person families, the young and those living outside of major cities are all less likely to be insured. Lifestyle factors have different impacts on insurance choice. Factors for the 'average' and 'driven' types are insignificant. Having 'bad' lifestyles lower the probability of insurance, while 'lazy' and 'aspirational' lifestyles raise it. These results are broadly consistent with an association between risky behaviours and lower risk aversion. The insurance premium and Medicare Levy Surcharge have the expected signs but are insignificant. One possible explanation for this could be measurement error in the insurance premium because without data on actual premiums we assume individuals choose a standard plan with a given co-payment and adjust the effective premium for the impact of policy rules. The adjustments are highly correlated with other controls included in the models particularly income. An alternative explanation could be the relatively low level of insurance premiums in Australia compared to other countries like the US or UK and the price insensitivity of consumers. The introduction of the insurance rebate in 1999, for instance, had almost no impact on insurance take-up of the population (Private Health Insurance Administration Council, 2004).

Focusing on model 2, we find that expected waiting time has a negative and significant coefficient and that expected probability of a long wait has a positive and significant coefficient.[6] At mean values, the elasticities of insurance to expected wait and probability of a long wait are -0.396 and 0.263, respectively.

Figure 2

Figure 2 shows the predicted insurance probability across the distribution of expected wait. The lower part of the figure shows the joint distribution of predicted expected wait and predicted long wait. For example, of those falling in the 10% of observations below the median of predicted expected wait, 42.6% also fall in the 10% of observations below the median of predicted long wait. The upper part of the figure plots the predicted impact on insurance across the distribution. The likelihood of a long wait is specified at: (i) its mean in a given percentile of expected wait (shown by dots connected with a dashed line, with an

[6] The expected waiting time is an imputed series however unlike the problem of generated regressors (see Pagan 1984), which involves predictions of variables within a data set, the actual waiting time variable is not available in the NHS data. Hence, the usual correction to the standard error of the coefficient estimate that involves residuals is not possible in this case. Fang *et al.* (2008) deal with a similar problem by assuming additive measurement error that is homoskedastic and independent. In our case, due to the extremely large sample size of the IWT data, the variance of the expected waiting time estimates is almost negligible (0.00000676). Nevertheless, in all models, White's heteroskedastic robust standard errors are used.

associated 95% confidence interval) and (ii) the distribution of long wait about the mean (scatter plots). All other variables are specified at their sample means. For comparison, we also plot predicted insurance without waiting time variables (solid line).

The scatter plots shows that although the probability of a long wait tends to move together with expected wait, there are individuals who are more likely to experience a long wait than an average person with similar expected wait: 7% of the sample have a predicted probability of insurance that is above the upper bound of the predicted probability for an individual with average probability of long wait. These individuals tend to be older, single females, in low income deciles, and *not* reporting their health as very good or excellent. Overall, waiting has a positive impact on insurance demand for 33% of the sample. For the majority of the population, on average, waiting time has no significant effect on insurance decision.

5 Conclusion

The aim of this study is to test the popular conjecture that waiting times in public hospitals drive private health insurance demand. Our approach is novel in the waiting time literature, in that we allow the expectation formation of waiting times to vary by individuals. To do this, we augment survey data with predictions of waiting times modelled using administrative data.

We find that in general expected waiting time has a negative impact on insurance purchase and that only a likelihood of wait in the very upper tail of the distribution increases the probability of insurance purchase. Overall we find there is no significant impact of waiting time on insurance purchase. There are however some subsets of the population who fall in the very upper tail of the distribution of waiting time, for whom waiting increases their predicted probability of buying insurance. One possible explanation for the high insurance rate in Australia not explored in this paper is that other aspects of quality such as doctor choice drive insurance demand more than waiting times.

Another key finding is that the inclusion of waiting time variables removes the independent positive effect of self assessed health on insurance demand. This suggests that part of the commonly found favourable selection effect of reported health status on insurance is due to concern about waiting time among healthier people.

6 References:

Asinski D. 2005. *Health Insurance, Access to Care, and Risk-Aversion: Separating Incentive and Selection Effects*. unpublished manuscript, Iowa State University.

Asplin BR, Rhodes KV, Levy H, et al. 2005. Insurance Status and Access to Urgent Ambulatory Care Follow-up Appointments. *Journal of the American Medical Association* **294 :** 1248–1254.

Besley T., Hall J., Preston I. 1999. The Demand for Private Health Insurance: Do Waiting Lists Matter? *Journal of Public Economics* **72**:155-181.

Buchmueller T, Fiebig D, Jones G, Savage E. 2008. Advantageous selection in private health insurance: The case of Australia. *CHERE Working Papers 2008/2*. University of Technology, Sydney.

Cardon JH, Hendel I. 2001. Asymmetric Information in Health Insurance: Evidence from the National Medical Expenditure Survey. *The RAND Journal of Economics* **32 (3):** 408-427.

Colombo F, Tapay N. 2004. Private Health Insurance in Ireland: A Case Study. *OECD Health Working Paper No.10*.

Costa J, Garcia J. 2003. Demand for Private Health Insurance: How Important is the Quality Gap? *Health Economics* **12(7)**: 587-599.

Costa-Font J, Font-Vilalta M. 2004. Preference for National Health Service Use and the Demand for Private Health Insurance in Spain. *Geneva Papers on Risk and Insurance Issues and Practices* **29(4)**: 705-718.

Cullis JG, Jones PR. 1986. Rationing by Waiting Lists: An Implication. *American Economic Review* **76(1)**: 250-256.

Doiron D, Jones G, Savage, E. 2008. Healthy, Wealthy and Insured? The Role of Self-Assessed Health in the Demand for Private Health Insurance. *Health Economics* **17(3)**: 317- 334.

Ellis R, Savage E. 2008. Run for Cover Now or Later? The Impact of Premiums, Threats and Deadlines on Supplementary Private Health Insurance in Australia. *International Journal of Health Care Finance and Economics* **8**: 257-277.

Fang H, Keane PM, Silverman D. 2008. Sources of Advantageous Selection: Evidence from the Medigap Insurance Market. *Journal of Political Economy* **116(2)**: 303-350.

Fiebig D, Savage E, Viney R. 2006. Does the Reason for Buying Health Insurance Influence Behaviour? *CHERE Working Paper 2006/1*, University of Technology, Sydney.

Harmon C, Nolan B. 2001. Health Insurance and Health Services Utilization in Ireland. *Health Economics* **10**: 135-145.

Hurd, MD. McGarry K. 1997. Medical Insurance and the Use of Health Care Services by the Elderly. *Journal of Health Economics* **16(2)**: 129-154

Jofre-Bonet M. 2000. Public Health Care and Private Insurance Demand: The Waiting Time as a Link. *Health Care Management Science* **3**: 51-71.

Johannesson M, Johansson P, Soderqvist T. 1998, Time Spent on the Waiting List for Medical Care: An Insurance Approach. *Journal of Health Economics* **17**: 627-644.

King D, Mossialos E. 2005. The Determinants of Private Medical Insurance Prevalence in England, 1997-2000**.** *Health Services Res*earch **40(1)**: 195-212.

Leung G, Yeung R, McGhee S, Johnston J. 2004. Waiting time and doctor shopping in a mixed medical economy. *Health Economics* **13(11)**: 1137-1144

Lindsay CM, Feigenbaum B. 1984, Rationing by Waiting Lists. *American Economic Review* **74(3)**: 404-417.

Lungen M, Stollenwerk B, Messner P, Lauterbach KW, Gerber A. 2008. Waiting Times for Elective Treatments According to Insurance Status: A Randomized Empirical Study in Germany. *International Journal for Equity in Health* **7(1)**: pages

Martin S, Smith P. 1999. Rationing by waiting lists: and empirical investigation. *Journal of Public Economics* **71**:141-164

Pagan A. 1984. Econometric Issues in the Analysis of Regressions with Generated Regressors. *International Economic Review* **25(1)**: 221-247.

Private Health Insurance Administration Council. 2004. Report on the Operations of the Registered Health Benefits Organisations. 2004. Commonwealth of Australia [http://www.phiac.gov.au]

Propper C. 1989. An Econometric Analysis of the Demand for Private Health Insurance in England and Wales. *Applied Economics* 21: 777-792

Propper C. 1990. Contingent Valuation of Time Spent on NHS Waiting Lists. *Economic Journal* **100**: 193-199.

Propper C. 1995. The disutility of time spent on the United Kingdom's National Health Service waiting lists. *Journal of Human Resources* **30**: 677-700.

Savage E, Wright D. 2003. Moral Hazard and Adverse Selection in Australian Private Hospitals: 1989-90. *Journal of Health Economics* **22**; 331-359.

Shmueli A. 2001. The Effect of Health on Acute Care Supplemental Insurance Ownership: An Empirical Analysis. *Health Economics* **10**:341-350

Viscusi WK, Evans WN. 1009. Utility Functions That Depend on Health Status: Estimates and Economic Implications. *American Economic Review* **80(3)**: 353-374.

Wang EC, Choe MC, Meara JG, Koempel JA. 2004. Inequality of Access to Surgical Specialty Health Care: Why Children With Government-Funded Insurance Have Less Access than Those With Private Insurance in Southern California. *Pediatrics* **114**; e584–e590.

Table I: IWT health factor loadings

	IWT factor 1	IWT factor 2	IWT factor 3	IWT factor 4	IWT factor 5	IWT factor 6	IWT factor 7	IWT factor 8	IWT factor 9	IWT factor 10	IWT factor 10	IWT factor 1
Malignant neoplasm	0.054	-0.199	-0.090	0.008	-0.681	-0.126	0.238	0.104	-0.131	0.127	-0.191	-0.026
Benign neoplasm	-0.324	-0.098	-0.407	-0.060	-0.167	0.208	-0.037	0.040	-0.023	-0.089	-0.157	0.013
Diabetes	0.525	-0.075	-0.328	-0.188	0.102	-0.040	0.022	0.065	0.011	-0.303	0.014	-0.057
Mental disorders	0.050	0.212	0.018	0.381	0.027	0.205	0.324	-0.154	-0.114	-0.111	0.005	0.109
Eye diseases	0.316	0.095	0.010	-0.571	0.304	-0.158	0.319	-0.251	-0.094	0.115	0.003	0.089
Ear diseases	0.040	0.062	0.109	0.096	0.077	-0.201	0.344	0.054	0.495	-0.095	-0.318	-0.032
Parasitic diseases	-0.089	-0.002	0.111	0.204	0.112	-0.264	0.266	0.136	0.501	-0.197	-0.099	-0.029
Heart diseases	0.642	0.084	-0.275	-0.018	0.033	-0.041	-0.014	0.133	-0.044	-0.049	-0.051	-0.003
Nervous system	0.219	0.203	0.228	0.113	-0.052	0.214	-0.064	-0.271	-0.065	-0.368	0.003	-0.070
Varicose veins	-0.014	0.023	0.064	0.003	-0.059	-0.156	0.036	0.088	0.211	0.079	0.837	-0.012
Stomach diseases	-0.246	0.324	-0.505	0.367	0.165	-0.262	-0.239	-0.190	-0.002	-0.012	0.056	0.020
Respiratory problems	0.121	0.198	0.026	0.215	0.147	-0.141	0.136	0.410	-0.358	0.229	-0.083	-0.038
Skin diseases	0.007	-0.023	0.160	-0.008	-0.466	-0.046	0.242	0.123	-0.058	-0.122	0.189	0.012
Bone diseases	0.340	0.353	0.307	0.073	-0.204	0.158	-0.302	0.063	0.121	-0.014	-0.063	0.040
Urinary system	0.264	-0.548	0.053	0.257	0.161	0.103	-0.105	0.007	0.072	0.075	-0.037	0.049
Congenital abnormalities	-0.001	-0.033	0.082	0.126	0.133	0.234	0.148	-0.163	0.057	0.269	0.107	-0.507
Fractures	0.002	0.208	0.383	-0.141	-0.061	0.027	-0.450	0.062	0.125	-0.016	-0.166	-0.085
Anaemia	0.013	0.005	-0.334	0.121	-0.132	0.155	-0.073	-0.074	0.260	0.095	-0.027	-0.057
Metabolic disorders	0.147	0.100	-0.204	0.082	0.088	0.244	-0.015	0.483	0.041	-0.237	0.112	-0.153
Thyroid gland	0.121	0.183	-0.081	0.050	0.029	0.268	0.084	0.332	0.059	0.270	0.012	-0.065
Alcohol & drug	-0.201	0.103	0.254	0.126	0.208	-0.336	0.000	0.298	-0.317	-0.049	-0.064	-0.030
Epilepsy	0.016	0.140	0.088	0.256	0.029	0.223	0.335	-0.281	-0.230	-0.055	-0.014	-0.164
Migraine	-0.017	0.068	0.034	0.123	0.026	0.176	0.102	0.034	-0.015	-0.149	0.102	0.738
Osteoporosis	0.153	0.226	-0.014	0.017	-0.011	0.154	0.052	-0.030	0.217	0.592	-0.073	0.287
Diseases of female organs	-0.350	-0.270	0.114	-0.196	0.298	0.480	0.103	0.249	0.025	-0.082	-0.021	0.061
Diseases of male organs	0.168	-0.428	0.097	0.315	0.129	-0.153	-0.173	-0.061	-0.077	0.144	-0.062	0.132
All other symptoms	0.366	-0.322	0.128	0.254	-0.020	0.000	-0.052	-0.052	-0.014	-0.017	0.105	-0.011

Table II: Means of IWT variables

Variable	Mean	Std. Dev.	Min	Max
Waiting time (days)	97.120	154.621	1	2820
Wait>P90	0.100	0.300	0	1
Male	0.448	0.497	0	1
Age<20	0.011	0.103	0	1
Age 20-24	0.035	0.184	0	1
Age 25-29	0.042	0.201	0	1
Age 30-34	0.056	0.230	0	1
Age 35-39	0.060	0.237	0	1
Age 45-49	0.073	0.260	0	1
Age 50-54	0.072	0.259	0	1
Age 55-59	0.083	0.276	0	1
Age 60-64	0.086	0.281	0	1
Age 65-69	0.103	0.303	0	1
Age 70-74	0.107	0.309	0	1
Age 75-79	0.105	0.307	0	1
Age 80-84	0.059	0.235	0	1
Age 85+	0.038	0.192	0	1
Male*age<20	0.005	0.072	0	1
Male*age 20-24	0.014	0.119	0	1
Male*age 25-29	0.016	0.127	0	1
Male*age 30-34	0.020	0.141	0	1
Male*age 35-39	0.022	0.147	0	1
Male*age 45-49	0.029	0.167	0	1
Male*age 50-54	0.031	0.174	0	1
Male*age 55-59	0.038	0.192	0	1
Male*age 60-64	0.043	0.202	0	1
Male*age 65-69	0.053	0.223	0	1
Male*age 70-74	0.055	0.229	0	1
Male*age 75-79	0.056	0.229	0	1
Male*age 80-84	0.024	0.154	0	1
Male*age 85+	0.014	0.116	0	1
No conditions	0.041	0.197	0	1
2 conditions	0.304	0.460	0	1
3 conditions	0.212	0.409	0	1
4 conditions	0.117	0.321	0	1
5 conditions	0.049	0.215	0	1
Major city	0.480	0.500	0	1
Inner region	0.361	0.480	0	1
N	175218			

Table III: IWT models for waiting time and long wait

	Wait time		Long wait	
	Coeff.	Std. Err.	Coeff.	Std. Err.
IWT factor1	-0.052	0.477	0.0027	0.0009***
IWT factor2	-6.066	0.376***	-0.0100	0.0007***
IWT factor3	12.221	0.367***	0.0210	0.0007***
IWT factor4	-32.706	0.380***	-0.0613	0.0007***
IWT factor5	1.486	0.369***	0.0059	0.0007***
IWT factor6	-15.939	0.377***	-0.0214	0.0007***
IWT factor7	-5.010	0.373***	-0.0071	0.0007***
IWT factor8	5.323	0.391***	0.0079	0.0008***
IWT factor9	0.164	0.361	0.0013	0.0007*
IWT factor10	5.006	0.373***	0.0099	0.0007***
IWT factor11	6.139	0.357***	0.0058	0.0007***
IWT factor12	-0.594	0.357*	-0.0017	0.0007**
Male	3.902	2.784	0.0041	0.0054
Age<20	-2.784	5.035	0.0056	0.0098
Age 20-24	-8.146	3.020***	-0.0063	0.0059
Age 25-29	-12.550	2.797***	-0.0152	0.0055***
Age 30-34	-10.697	2.551***	-0.0122	0.0050**
Age 35-39	-4.323	2.513*	-0.0076	0.0049
Age 45-49	1.144	2.416	-0.0015	0.0047
Age 50-54	1.882	2.465	0.0058	0.0048
Age 55-59	0.837	2.423	0.0046	0.0047
Age 60-64	6.004	2.455**	0.0074	0.0048
Age 65-69	13.424	2.391***	0.0263	0.0047***
Age 70-74	14.576	2.396***	0.0347	0.0047***
Age 75-79	14.977	2.428***	0.0343	0.0047***
Age 80-84	11.699	2.660***	0.0301	0.0052***
Age 85+	-10.892	2.934***	-0.0072	0.0057
Male*age<20	-5.993	7.378	-0.0063	0.0144
Male*age 20-24	0.327	4.749	0.0120	0.0093
Male*age 25-29	8.791	4.494**	0.0213	0.0088**
Male*age 30-34	11.412	4.170***	0.0195	0.0081**
Male*age 35-39	5.467	4.085	0.0154	0.0080*
Male*age 45-49	0.960	3.856	0.0098	0.0075
Male*age 50-54	-5.403	3.840	-0.0059	0.0075
Male*age 55-59	-5.661	3.711	-0.0079	0.0072
Male*age 60-64	-11.075	3.680***	-0.0113	0.0072
Male*age 65-69	-13.946	3.554***	-0.0220	0.0069***
Male*age 70-74	-9.951	3.531***	-0.0209	0.0069***
Male*age 75-79	-10.902	3.542***	-0.0189	0.0069***
Male*age 80-84	-10.088	4.076***	-0.0169	0.0080**
Male*age 85+	6.704	4.702	0.0102	0.0092

Table III: IWT models for waiting time and long wait (continued)

	Wait time		Long wait	
	Coeff.	Std. Err.	Coeff.	Std. Err.
No conditions	-28.009	1.911***	-0.0400	0.0037***
2 conditions	7.157	0.974***	0.0137	0.0019***
3 conditions	12.046	1.197***	0.0207	0.0023***
4 conditions	17.160	1.576***	0.0256	0.0031***
5 conditions	25.355	2.224***	0.0380	0.0043***
Major city	3.874	1.041***	0.0109	0.0020***
Inner region	8.377	1.073***	0.0190	0.0021***
Constant	82.176	2.053***	0.0664	0.0040***
N	175,218		175,218	
R-sq	0.075		0.063	

Note: *, **, *** denotes p-values less than 10%, 5% and 1%, respectively.

Table IV: NHS health factor loadings

	NHS factor 1	NHS factor 1	NHS factor 1	NHS factor 1	NHS factor 1	NHS factor 1	NHS factor 17	NHS factor 1	NHS factor 1	NHS factor 1
Malignant neoplasm	0.182	0.008	0.143	-0.053	-0.115	0.422	-0.229	0.061	0.11	-0.127
Benign neoplasm	0.192	0.021	-0.199	0.081	-0.329	-0.056	-0.072	-0.05	0.551	-0.005
Diabetes	0.322	-0.321	0.177	-0.066	-0.106	0.133	0.287	0.151	-0.26	-0.115
Mental disorders	0.248	0.541	0.106	0.272	-0.114	-0.058	-0.074	0.023	-0.151	0.009
Eye diseases	0.474	-0.204	0.003	0.067	0.081	-0.227	-0.088	0.033	0.009	-0.158
Ear diseases	0.423	-0.088	0.337	-0.047	0.209	-0.133	0.039	0.071	0.002	-0.1
Parasitic diseases	0.111	0.271	0.38	-0.142	-0.268	0.04	0.168	0.171	0.289	0.251
Heart diseases	0.56	-0.311	0.138	-0.084	-0.011	0.065	0.002	0.07	-0.118	0.101
Nervous system	0.249	0.203	0.113	0.004	-0.157	0.004	0.111	-0.248	0.16	-0.264
Varicose veins	0.246	-0.065	-0.215	-0.21	0.098	0.216	-0.392	-0.164	-0.047	0.468
Stomach diseases	0.421	0.057	-0.114	-0.01	0.017	0.061	0.035	-0.237	-0.122	0.178
Respiratory problems	0.332	0.347	-0.175	-0.118	0.004	0.157	-0.006	0.185	0.079	-0.106
Skin diseases	0.081	0.036	-0.264	-0.115	0.002	0.266	0.469	-0.294	0.018	0.376
Bone diseases	0.582	-0.069	0.014	-0.048	0.116	0.028	-0.072	0.047	-0.12	0.103
Urinary system	0.366	-0.018	-0.136	0.202	-0.162	0.023	-0.086	-0.143	0.1	-0.239
Congenital abnormalities	0.098	0.225	-0.241	-0.331	0.374	-0.042	0.072	0.343	-0.034	-0.156
Fractures	0.165	0.199	-0.154	-0.035	0.409	0.044	0.35	-0.361	0.125	-0.248
Anaemia	0.23	0.115	-0.02	0.054	-0.28	0.37	0.222	0.011	-0.144	-0.193
Metabolic disorders	0.139	0.004	-0.29	0.043	-0.215	-0.404	0.29	0.18	-0.236	0.019
Thyroid gland	0.242	-0.068	-0.331	0.111	-0.143	-0.39	0.121	0.03	0.067	0.184
Alcohol & drug	0.073	0.451	0.22	0.163	-0.162	-0.174	-0.127	-0.184	-0.415	0.183
Epilepsy	0.083	0.289	0.205	-0.229	0.262	-0.243	-0.153	-0.347	0.012	-0.078
Migraine	0.121	0.414	-0.254	-0.144	0.05	0.047	-0.119	0.444	0.053	0.065
Osteoporosis	0.417	-0.161	-0.068	0.093	0.048	-0.15	-0.258	-0.046	0.185	-0.008
Diseases of female organs	0.018	0.018	0.034	0.547	0.326	0.014	0.111	0.11	0.238	0.212
Diseases of male organs	0.094	0.007	0.442	-0.302	0.013	-0.228	0.246	0.07	0.273	0.246
All other symptoms	0.107	0.052	0.158	0.502	0.325	0.216	0.106	0.188	0.009	0.136

Table V: Covariate means for the NHS sample

	Mean	Std.Dev.		Mean	Std.Dev.
Predicted annual premium ($'00)	7.474	5.593	Age 45-49	0.096	0.295
MLS > premium	0.087	0.283	Age 50-54	0.081	0.273
Income decile 1^	0.110	0.312	Age 55-59	0.080	0.272
Income decile 2	0.110	0.313	Age 60-64	0.067	0.250
Income decile 3	0.078	0.268	Age 65-69	0.058	0.233
Income decile 4	0.071	0.256	Age 70-74	0.054	0.227
Income decile 5	0.071	0.257	Age 75-79	0.043	0.203
Income decile 6	0.071	0.256	Age 80-84	0.032	0.176
Income decile 7	0.077	0.267	Age 85+	0.018	0.133
Income decile 8	0.080	0.272	Number of children	0.634	0.984
Income decile 9	0.092	0.289	Single person, male	0.158	0.364
Income decile 10	0.103	0.304	Single person, female	0.190	0.392
Income missing	0.138	0.345	Sole parent	0.066	0.249
Postgraduate	0.181	0.385	Couple with dependant	0.268	0.443
Undergraduate	0.123	0.328	Couple only^	0.319	0.466
Some post-school	0.243	0.429	Foreign born	0.297	0.457
No post-school^	0.453	0.498	High exercise^	0.053	0.223
Major city	0.706	0.456	Moderate exercise	0.225	0.418
Inner regional	0.199	0.399	Low exercise	0.354	0.478
Outer^	0.095	0.293	No exercise	0.368	0.482
SAH: excellent^	0.182	0.386	Underweight	0.024	0.154
SAH: very good	0.337	0.473	Normal weight^	0.402	0.490
SAH: good	0.291	0.454	Overweight	0.318	0.466
SAH: fair	0.133	0.339	Obese	0.171	0.377
SAH: poor	0.058	0.233	Missing weight	0.085	0.279
# conditions	1.603	1.553	Smoker	0.231	0.422
Age<20	0.022	0.146	Alcohol: non drinker^	0.190	0.393
Age 20-24	0.065	0.247	Alcohol: <1 last week	0.210	0.407
Age 25-29	0.075	0.263	Alcohol: low risk	0.288	0.453
Age 30-34	0.096	0.295	Alcohol: med risk	0.150	0.357
Age 35-39	0.106	0.307	Alcohol: high risk	0.162	0.368
Age 40-44^	0.107	0.308	Glasses	0.613	0.487
			N	3989	

Note: ^ reference group omitted in regression.

Table VI: Probit estimates of hospital admission model

Variable	Coef.	Std. Err.	P>|z|
NHS factor1	0.248	0.069	0.000
NHS factor2	0.107	0.034	0.002
NHS factor3	0.088	0.032	0.007
NHS factor4	0.047	0.037	0.205
NHS factor5	0.098	0.030	0.001
NHS factor6	-0.015	0.024	0.530
NHS factor7	0.037	0.023	0.100
NHS factor8	0.029	0.031	0.352
NHS factor9	0.010	0.026	0.704
NHS factor10	0.016	0.024	0.515
SAH: very good	-0.025	0.077	0.745
SAH: good	0.147	0.080	0.064
SAH: fair	0.306	0.098	0.002
SAH: poor	0.698	0.121	0.000
Age<20	0.228	0.187	0.222
Age 20-24	0.357	0.123	0.004
Age 25-29	0.438	0.115	0.000
Age 30-34	0.275	0.111	0.014
Age 35-39	-0.092	0.116	0.429
Age 45-49	0.052	0.115	0.649
Age 50-54	-0.053	0.121	0.659
Age 55-59	0.015	0.119	0.901
Age 60-64	0.147	0.125	0.237
Age 65-69	0.104	0.130	0.422
Age 70-74	0.044	0.136	0.746
Age 75-79	0.103	0.145	0.476
Age 80-84	0.282	0.154	0.067
Age 85+	0.012	0.202	0.954
Foreign born	-0.173	0.059	0.003
Male	-0.170	0.053	0.001
# conditions	-0.080	0.058	0.168
Moderate exercise	0.140	0.127	0.268
Low exercise	0.095	0.123	0.441
No exercise	0.078	0.126	0.538
Smoker	-0.089	0.062	0.150
Alcohol: <1 last week	-0.130	0.077	0.093
Alcohol: low risk	-0.124	0.074	0.096
Alcohol: med risk	-0.144	0.088	0.099
Alcohol: high risk	-0.096	0.088	0.274
Underweight	0.136	0.149	0.363
Overweight	0.004	0.059	0.948
Obese	0.024	0.071	0.740
Missing weight	-0.228	0.096	0.018
Major city	0.036	0.084	0.668
Inner regional	0.141	0.093	0.130
Constant	-0.977	0.200	0.000
Log-L	-1718.7		
N	3989		
Pseudo R-sq	0.077		
Wald test (p-value)	278.47 (0.00)		

Note: White's heteroskedastic robust standard errors are used. NHS factors are not the same as IWTfactors. NHSfactors are derived from NHS sample and IWTfactors are derived from IWT data.

Table VII: Lifestyle factors (NHS sample)

	Life Factor 1	Life Factor 2	Life Factor 3	Life Factor 4	Life Factor 5
Exercise (0 none to 3 high intensity)	0.438	0.138	-0.385	0.400	0.522
Underweight	-0.241	-0.160	0.151	-0.559	0.693
Overweight	0.681	-0.474	0.023	-0.190	-0.296
Obese	-0.448	0.545	-0.518	-0.135	-0.209
Missing weight	-0.367	-0.066	0.564	0.649	0.061
Smoker	0.131	0.501	0.546	-0.300	-0.231
Alcohol (0 none to 4 high risk)	0.489	0.526	-0.012	0.122	0.049
Glasses	-0.293	-0.414	-0.340	0.079	-0.257

Note: the sample size is 3989.

Table VIII: NHS means by insurance status

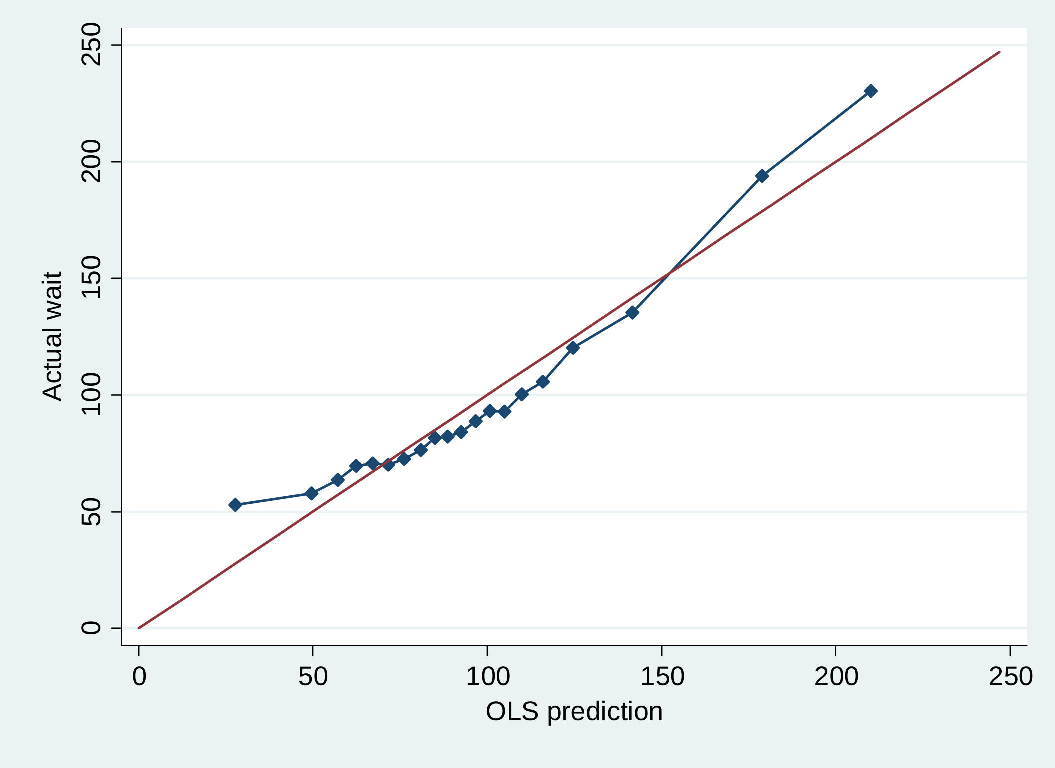
	All		Uninsured		Insured	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Insurance	0.450	0.498				
E(w)*Pr(adm)	14.860	11.628	16.194	12.420	13.227	10.349
Pr(long wait)*Pr(adm)	0.014	0.014	0.015	0.014	0.013	0.012
Predicted annual premium ($'00)	7.474	5.593	8.034	4.920	6.788	6.253
MLS > premium	0.087	0.283	0.036	0.186	0.151	0.358
Income decile 1 (base)	0.110	0.312	0.159	0.366	0.049	0.216
Income decile 2	0.110	0.313	0.164	0.370	0.043	0.204
Income decile 3	0.078	0.268	0.103	0.303	0.047	0.213
Income decile 4	0.071	0.256	0.082	0.275	0.056	0.231
Income decile 5	0.071	0.257	0.077	0.267	0.064	0.244
Income decile 6	0.071	0.256	0.072	0.258	0.070	0.255
Income decile 7	0.077	0.267	0.071	0.256	0.085	0.279
Income decile 8	0.080	0.272	0.064	0.245	0.100	0.301
Income decile 9	0.092	0.289	0.062	0.240	0.129	0.335
Income decile 10	0.103	0.304	0.038	0.191	0.182	0.386
Income missing	0.138	0.345	0.109	0.312	0.174	0.379
Postgraduate	0.181	0.385	0.106	0.308	0.273	0.446
Undergraduate	0.123	0.328	0.108	0.311	0.140	0.348
Some post-school	0.243	0.429	0.252	0.434	0.232	0.422
No post-school (base)	0.453	0.498	0.533	0.499	0.354	0.478
Major city	0.706	0.456	0.653	0.476	0.771	0.420
Inner regional	0.199	0.399	0.226	0.418	0.166	0.372
Outer	0.095	0.293	0.121	0.326	0.064	0.244
Lifestyle factor 1	0.000	1.000	0.009	0.993	-0.011	1.008
Lifestyle factor 2	0.000	1.000	0.140	1.061	-0.171	0.891
Lifestyle factor 3	0.000	1.000	-0.066	1.080	0.080	0.886
Lifestyle factor 4	0.000	1.000	-0.160	0.985	0.195	0.984
Lifestyle factor 5	0.000	1.000	0.021	1.039	-0.025	0.950
SAH: excellent (base)	0.337	0.473	0.149	0.356	0.222	0.416
SAH: very good	0.291	0.454	0.298	0.458	0.384	0.486
SAH: good	0.133	0.339	0.311	0.463	0.268	0.443
SAH: fair	0.058	0.233	0.162	0.369	0.096	0.295
SAH: poor	0.337	0.473	0.080	0.271	0.031	0.172
Age 20-34	0.258	0.438	0.301	0.459	0.206	0.404
Age 35-49 (base)	0.308	0.462	0.281	0.450	0.342	0.474
Age 50-64	0.228	0.420	0.184	0.387	0.283	0.450
Age 65-79	0.155	0.362	0.170	0.376	0.137	0.343
Age 80+	0.050	0.218	0.064	0.244	0.033	0.180
Number of children	0.634	0.984	0.637	0.995	0.631	0.971
Single person, male	0.158	0.364	0.188	0.391	0.120	0.326
Single person, female	0.190	0.392	0.218	0.413	0.155	0.362
Sole parent	0.066	0.249	0.097	0.295	0.029	0.168
Couple with dependants	0.268	0.443	0.224	0.417	0.322	0.467
Couple only without dependant (base)	0.319	0.466	0.273	0.446	0.374	0.484
Foreign born	0.297	0.457	0.317	0.465	0.273	0.446
N	3989		2195		1794	

Table IX: OLS estimates of the insurance demand model

	Model 1		Model 2		Model 3	
	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
E(w)*Pr(adm)			-0.012	(0.002)***	-0.008	(0.003)***
Pr(long wait)*Pr(adm)			8.464	(2.257)***	6.754	(2.400)***
Predicted premium	-0.002	(0.003)	-0.002	(0.003)	-0.002	(0.003)
MLS > premium	0.041	(0.038)	0.041	(0.038)	0.042	(0.038)
Income decile 2	-0.040	(0.026)	-0.040	(0.026)	-0.041	(0.026)
Income decile 3	0.060	(0.030)**	0.061	(0.030)**	0.059	(0.030)*
Income decile 4	0.102	(0.034)***	0.105	(0.034)***	0.100	(0.034)***
Income decile 5	0.153	(0.034)***	0.154	(0.034)***	0.149	(0.034)***
Income decile 6	0.200	(0.034)***	0.201	(0.035)***	0.198	(0.034)***
Income decile 7	0.248	(0.034)***	0.247	(0.034)***	0.243	(0.034)***
Income decile 8	0.298	(0.034)***	0.300	(0.034)***	0.294	(0.034)***
Income decile 9	0.345	(0.034)***	0.344	(0.034)***	0.339	(0.034)***
Income decile 10	0.410	(0.043)***	0.408	(0.043)***	0.404	(0.044)***
Income missing	0.273	(0.039)***	0.271	(0.039)***	0.270	(0.039)***
Postgraduate	0.143	(0.022)***	0.146	(0.022)***	0.144	(0.022)***
Undergraduate	0.053	(0.024)**	0.058	(0.024)**	0.054	(0.024)**
Some post-school	0.021	(0.018)	0.022	(0.018)	0.022	(0.018)
Major city	0.124	(0.024)***	0.116	(0.024)***	0.118	(0.024)***
Inner regional	0.042	(0.026)	0.042	(0.027)	0.039	(0.027)
Age 20-34	-0.141	(0.019)***	-0.124	(0.019)***	-0.132	(0.020)***
Age 50-64	0.111	(0.022)***	0.106	(0.023)***	0.109	(0.023)***
Age 65-79	0.096	(0.028)***	0.076	(0.031)**	0.077	(0.031)**
Age 80+	0.031	(0.040)	0.018	(0.041)	0.014	(0.041)
Number of children	-0.009	(0.012)	-0.009	(0.012)	-0.010	(0.012)
Single person, male	-0.128	(0.026)***	-0.139	(0.026)***	-0.134	(0.026)***
Single person, female	-0.099	(0.026)***	-0.094	(0.026)***	-0.097	(0.026)***
Sole parent	-0.098	(0.036)***	-0.094	(0.036)***	-0.094	(0.036)***
Couple with dependant	0.078	(0.030)***	0.076	(0.030)**	0.078	(0.030)**
Foreign born	-0.100	(0.016)***	-0.112	(0.016)***	-0.107	(0.016)***
Lifestyle factor 1	0.003	(0.007)	0.003	(0.007)	0.004	(0.007)
Lifestyle factor 2	-0.054	(0.008)***	-0.059	(0.008)***	-0.056	(0.008)***
Lifestyle factor 3	0.023	(0.007)***	0.027	(0.007)***	0.025	(0.007)***
Lifestyle factor 4	0.034	(0.008)***	0.037	(0.008)***	0.034	(0.008)***
Lifestyle factor 5	0.008	(0.007)	0.010	(0.007)	0.009	(0.007)
SAH: very good	0.008	(0.020)			0.008	(0.020)
SAH: good	-0.047	(0.022)**			-0.039	(0.022)*
SAH: fair	-0.073	(0.026)***			-0.051	(0.029)*
SAH: poor	-0.108	(0.034)***			-0.057	(0.046)
Constant	0.223	(0.053)***	0.258	(0.052)***	0.257	(0.054)***
R-sq	0.25		0.25		0.26	
F (p-value)	62.46 (0.00)		66.99 (0.00)		60.26 (0.00)	

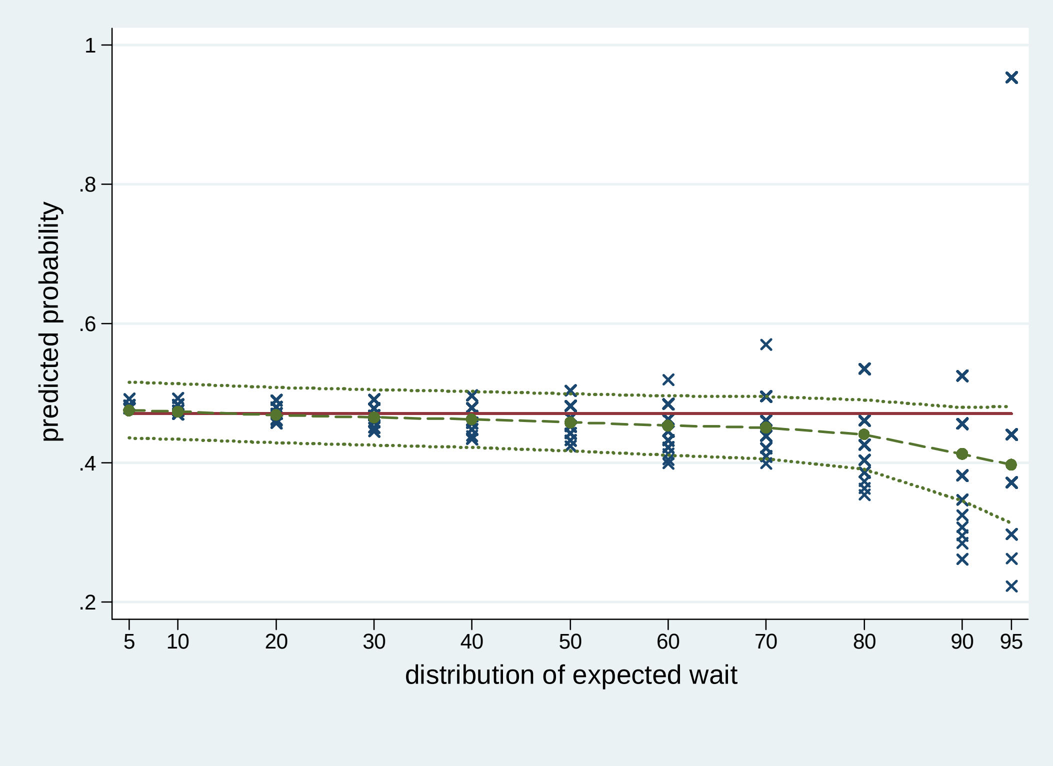
Note: *, **, *** denotes p-values less than 10%, 5% and 1%, respectively. The base groups for income, education, location, self-assessed health (SAH), age and income unit type are: the lowest income group, no post school qualification, outer regional, excellent health, age 35-49 and couple without dependant, respectively.

Figure 1: Fit of predicted waiting times (IWT sample)



Note: the straight line is a 45-degree line. Each point is the scatter plot of mean actual waiting time and
predicted waiting time for 5th, 10th, … 95th percentile of the predicted waiting time distribution.

Figure 2: Impact of expected wait and probability of a long wait on the predicted probability of insurance



Note: solid line represents the predicted probability from a model without waiting time variables. Connected circles and dotted lines represent the predicted insurance share at the mean of long wait (*p90*) holding the expected wait at its appropriate percentile; dotted lines show 95% confidence interval. Each marker "x" indicates the predicted insurance share at individuals' percentiles of long wait, holding the expected wait at its appropriate decile value. Heterogeneity within expected wait percentile is due to individuals with lower or higher percentile of long wait than the mean. The following table reports the representative weight (%) of each marker. * indicates empty cells.

	Distribution of expected wait										
Distribution of long wait	5	10	20	30	40	50	60	70	80	90	95
5	71.9	18.5	1.8	1.0	1.3	*	0.3	*	*	0.5	*
10	26.6	46.5	10.5	2.0	0.3	0.5	0.3	*	*	*	*
20	1.5	34.0	50.9	21.6	7.8	1.5	0.3	*	0.3	*	*
30	*	1.0	33.6	37.3	17.3	8.5	2.0	0.3	0.3	0.3	*
40	*	*	3.3	34.3	39.1	15.0	6.0	1.8	0.3	0.3	*
50	*	*	*	3.8	32.1	42.6	16.0	2.5	2.3	0.5	0.5
60	*	*	*	*	2.3	30.1	45.9	16.5	4.8	0.5	*
70	*	*	*	*	*	1.8	29.1	51.6	15.5	1.8	0.5
80	*	*	*	*	*	*	0.3	27.1	56.4	15.3	2.0
90	*	*	*	*	*	*	*	0.3	20.3	67.2	22.6
95	*	*	*	*	*	*	*	*	*	13.8	58.8
100	*	*	*	*	*	*	*	*	*	*	15.6