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# Waiting times and the decision to buy private health insurance

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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 $0 \le g(w) \le 1$, and $g(w+\Delta) - g(w) \le 0$, 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, $\alpha$. A market for health insurance sells contracts at an equilibrium fair premium $\pi$ (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 $\alpha$ 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 $\pi$, 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, $\alpha_j$ 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.

[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 5$^{th}$ 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)
$$E(w_j) = \hat{w}_j = \hat{\theta}_0 + \hat{\theta}_1 X_j + \hat{\theta}_2 Z_j$$
$$E(lw_j) = \hat{l}w_j = \hat{\delta}_0 + \hat{\delta}_1 X_j + \hat{\delta}_2 Z_j .$$

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:

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

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 $\psi_j$ 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 9$^{th}$ and 10$^{th}$ 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 $\vartheta$ 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.

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**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**

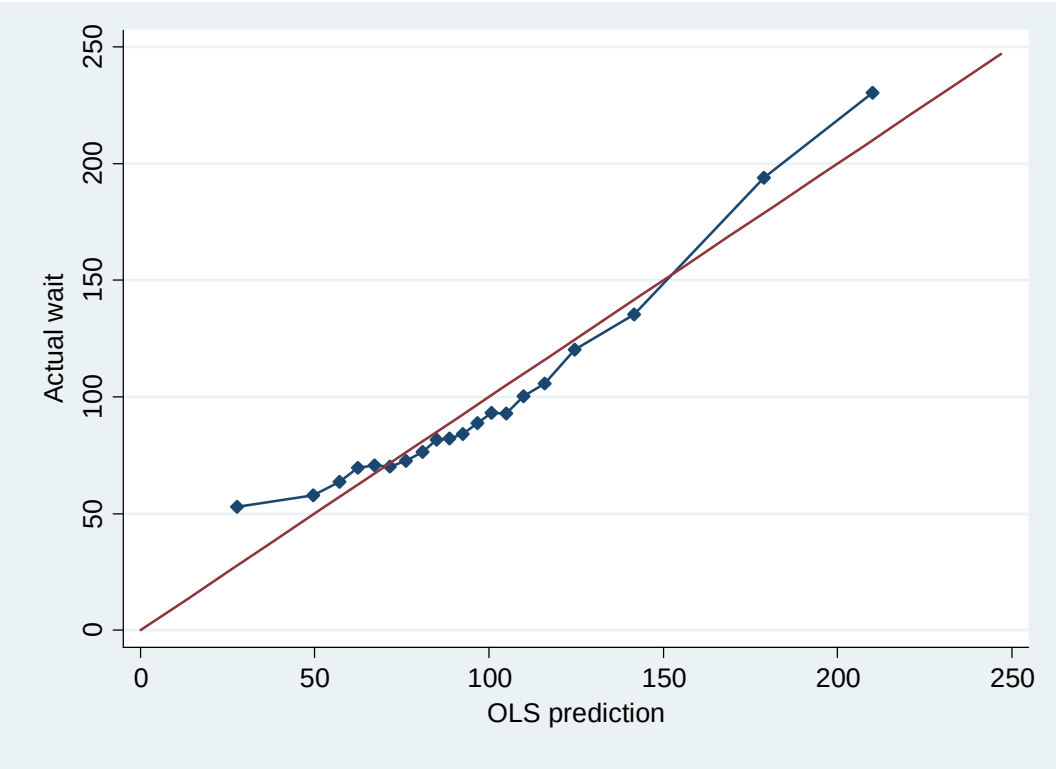
| | All | | Uninsured | | Insured | |
|---|---|---|---|---|---|---|
| Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Insurance | 0.450 | 0.498 | | | | |
| E(w)*Pr(adm) | 14.860 | 11.628 | 16.194 | 12.420 | 13.227 | 10.349 |
| Pr(long wait)*Pr(adm) | 0.014 | 0.014 | 0.015 | 0.014 | 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) | |

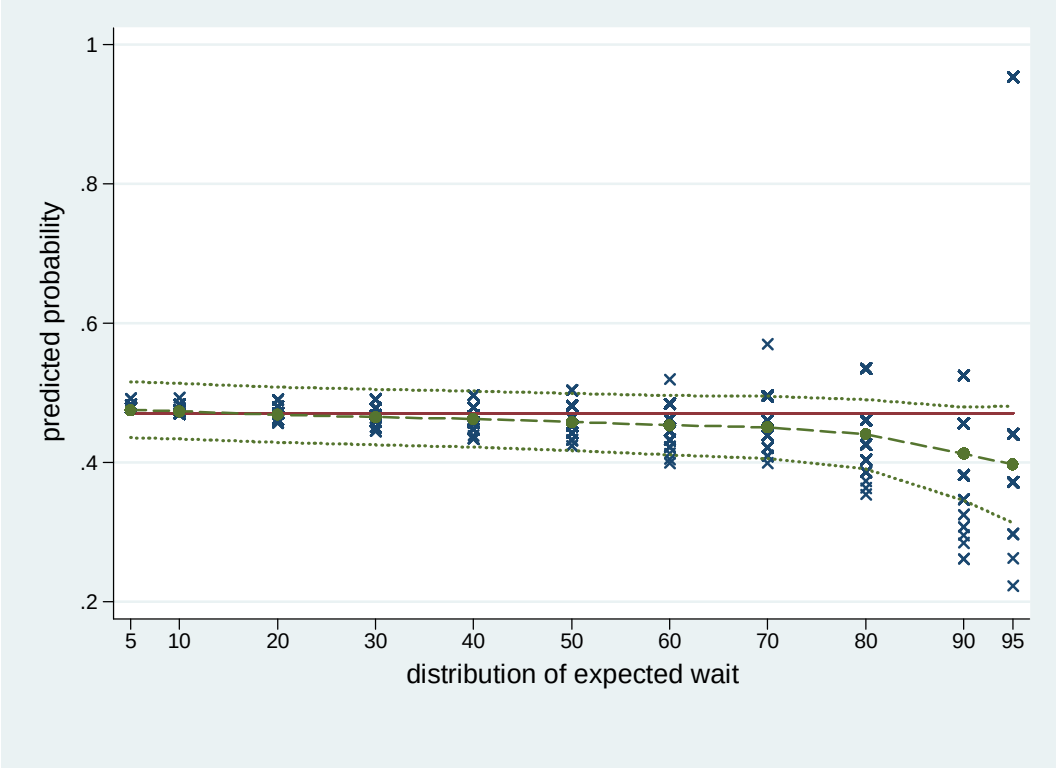
Note: *, **, *** denotes p-values less than 10%, 5% and 1%, respectively. The base groups for income, education, location, self-assessed health (SAH), age and income unit type are: the lowest income group, no post school qualification, outer regional, excellent health, age 35-49 and couple without dependant,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