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An analysis of mammography decisions with a focus on educational differences

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An analysis of mammography decisions with a focus on education differences
PRELIMINARY VERSION

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Abstract

I analyze the decisions on undertaking breast screening by women aged 50-64 in the UK. I provide estimation results on the discounting of the potential future benefits of screening. I also analyze the education differences in mammography decisions, and examine the underlying mechanism how education influences breast screening attendance. The reduced form estimation results suggest that the observed education gradient is mainly due to differences in health behaviors and health care attitudes. Using the institutional settings of the UK, I estimate a structural model, which reveals that although there are differences in the disutility of breast screening along the education level, there is no such difference in the estimated discount factor. I also find some evidence that women are forward looking when deciding on mammography attendance, and might even overestimate the potential benefits of mammography.

JEL Classification: C25, I11, I12

Keywords: mammography, health discount rate, education gradient

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1 Motivation and institutional background

Governments are taking effort in increasing the utilization of preventive care services. The aims of these measures are to improve health, to increase the expected lifetime, and also to reduce the health care expenditures due to acute medical treatment. Cancer screening programs are considered as preventive services, as not having curative role. The NHS (National Health Service) in the UK has three cancer screening programmes: breast screening, cervical screening, and bowel cancer screening programmes. In this paper my focus is on the utilization of breast screening services.

The start of breast screening programmes in the UK dates back to 1988. From then, women aged 50-64 are invited for breast screening every third year. The costs of the screening are covered by the NHS. Since 2004, the coverage of the screening programme has been extended to include women aged 65-70 years. Women aged over 70 can request mammography once every three years, but they are not routinely invited. The frequency of invitations and age categories are the same in England, Scotland, Wales, and Northern Ireland.[1] Because of the age restrictions on the target group, in the empirical analysis I focus on the utilization decisions of women aged 50-64. As the common method of breast screening is mammography, I use these two terms interchangeably in this paper.

There are some controversies about the benefits of breast screening. Based on US data, the Agency for Healthcare Research and Quality (2009) report that mammography screening reduces breast cancer mortality by around 15% for women aged 39-59 years. This reducing effect is larger (around 30%) for women aged 60-69. On the other hand, based on a meta-analysis Gotzsche and Olsen (2000) claim that there is no evidence that breast screening would decrease mortality due to breast cancer, and argue that screening for breast cancer with mammography is unjustified. The Cancer Research UK also overviews the controversy over the potential benefits of breast screening, citing wide range of estimated effects in mortality reduction, and suggesting that breast screening can save $500 - 1,400$ lives per year in the UK.[2]

I analyze the utilization of breast screening by adult women in the UK. My aim is to provide estimation results on the discounting of the potential future benefits of screening. I also focus on the education differences in mammography decisions, and examine the mechanism how education influences breast screening. My results provide policy-relevant conclusions on mitigating the education gradient in preventive care utilization, and I also find some evidence

[1] This summary of institutional background is based on the information provided by Cancer Research UK. Source: http://info.cancerresearchuk.org/cancerstats/types/breast/screening/history/

[2] Source: http://cancerhelp.cancerresearchuk.org/type/breast-cancer/about/screening/mammograms-in-breast-screening

that the mammography attendance rate might be higher than optimal.

It is well documented in the literature that health behaviors differ by education level, and people with higher education level are generally more likely to utilize preventive health services. This also holds for mammography: positive effect of education on mammography attendance is found among others by Cutler and Lleras-Muney (2010) for the UK and US, Maxwell et al. (1997) for Canada, and Lee and Vogel (1995) based on data from the Texas Breast Screening Project. However, Moser et al. (2009) do not find a significant effect of education level on breast screening based on data from the National Statistics Omnibus Survey of the UK. In this paper I find significantly positive effect of education level on mammography utilization only if a limited set of individual characteristics are controlled for, and this effect is estimated to be of relatively small magnitude. At the same time, there is also evidence in the literature for a positive association between education level and cancer survival (cancers in general, and also breast cancer in particular), see e.g. Albano et al. (2007), Hussain et al. (2007) for the US and Sweden, respectively. These educational differences can be due to differences in risk factors, in access to medical care after being diagnosed with cancer, and also in cancer screening.

The main contribution of my paper is the novel empirical analysis of mammography attendance. The paper also relates to the theoretical literature on health care utilization. The general framework of modelling health care demand has been set by Grossman (1972). Following his approach, it is can be assumed that health care utilization is based on the utility maximizing behavior of the individuals, and medical care improves health through a "health production" function. Phelps (1978) derives a model of demand for preventive health services. In his model the consumer maximizes a utility function of consumption and health, subject to the budget constraint. Different approaches to modelling preventive care utilization are provided by Ayyagari (2007) and Maurer (2009). Both authors analyze the determinants of the demand for vaccinations.

There is a relatively large number of papers which empirically analyze the utilization of preventive medical services, using individual level data. These studies typically focus on a specific aspect of preventive care demand, and apply cross sectional estimation methods. My paper extends this literature by making use of panel observations, and applying structural approach. In my empirical analysis I also take into consideration the institutional settings in the UK.

My reduced form estimations are related to Hofer and Katz (1996) and Jusot et al. (2011). Hofer and Katz (1996) analyze to what extent healthy behaviors explain the variation in preventive care utilization by women in the US and Canada. They find evidence for the relevance of healthy behavior, but the socioeconomic gradient in preventive care utilization remains even if healthy behavior is controlled for. Jusot et al. (2011) investigate the variations in preventive care utilization across 14 European countries. Their main findings are that higher educated and higher income groups use more preventive services, and public health expenditures and GP density are positively associated with preventive care use. Fletcher and Frisvold (2009) look at some channels how education might influence preventive care, and find that occupations with higher prestige and better access to care contribute to the effect of education.

The utilization of preventive care can be less than optimal if the decision makers do not fully take into account the future benefits of current utilization. There are few papers which address the issue of myopic behavior related to preventive care utilization. In this paper I take a simple step towards investigating the potentially myopic behavior in preventive care utilization via estimating the discount rate of health decisions. As my estimations indicate negative discount rate I find no empirical support for myopic behavior.

In this paper I use observed health behaviors of survey respondents to elicit their time preferences. Fuchs (1982) also addresses the relationship between health behaviors, health and time preferences, but he uses survey measures on time preferences for this empirical analysis. He finds evidence that time preference is related to schooling, and also to health investment and health status, even though these estimated relationships are weak. Fang and Wang (2010) provide an empirical analysis of preventive care utilization based on a dynamic discrete choice model, where individuals are allowed to have hyperbolic discounting, and to be naive about their time-inconsistency. Their application is also on mammography decisions, using data from the Health and Retirement Study. They find evidence both for present bias and naivety. My approach is a modified (in a sense simpler) version of Fang and Wang (2010), which is based on the institutional characteristics in the UK. My estimations lead to different conclusions.

Cutler and Lleras-Muney (2010) and Pol (2011) also investigate the relationship between education, health behaviors and time preferences. They use various data sets from the US, UK and the Netherlands, and find no evidence for differences in discounting or in risk aversion along the education level or for the hypothesis that different time preferences could explain the education-health gradient. My structural estimations can complement the analyses of Cutler and Lleras-Muney and Pol by estimating the discount factor based on observed health decisions, rather than using proxies for discounting when analyzing the education gradient in health behaviors.

The rest of the paper is organized as follows. In section 2 I describe the model that forms the basis of the empirical analysis. The data is presented in section 3, and the empirical results are discussed in section 4. Section 5 concludes.

2 Model

In this section I present a simple dynamic discrete choice model which forms the basis of my structural estimations. This is a semi-parametric model. An alternative approach could be to build a fully parametric model of preventive care utilization (e.g. following a similar approach as Picone et al. (1998)). The main drawback of this approach is the heavy dependence on the necessary functional form assumptions. Thus a fully parametric model could not be reliably used for the identification of the discount factor.

In the preferred semi-parametric model I take into consideration that preventive care utilization is a discrete (binary) choice, there are random preference shocks, and there are some institutional constraints. The following model is simpler than the related models of Hotz and Miller (1993) and Fang and Wang (2010). They estimate structural parameters of discrete choice dynamic programming problems with infinite time horizon. I assume finite time horizon, however, I can utilize the three year recommended frequency of breast screening when specifying the discrete choice model. Although Fang and Wang also apply their model to decisions on mammography, their approach is not applicable to the UK sample as in the UK women generally do not have to make decisions on mammography each year.

In my model the decision the individuals have to make is whether to attend a due screening or not. A screening is defined to be due if a woman in the target age category did not attend a screening during the previous two years. I assume that if a woman decides not to attend a due screening then this decision implies not attending a screening in that three year time period. If she decides to attend then she is again assumed to expect not attending a screening in the next two years. The main simplifying assumption is that the decision makers take into account only three years when deciding on attending breast screening. Although the limited time horizon is a restriction, that is necessary as survival probabilities with and without screening on longer time horizons cannot be reliable estimated because of the large ratio of attrition. In section 4.3 I check how sensitive the empirical results are to the restriction of two versus three years of time horizon, and also present alternative specifications with longer time horizon and with allowing for repeated and postponed screenings.

Let $i \in \{0, 1\}$ denote the choice options on utilization, $x \in X$ denote the observable state variables (e.g. age, education level), and $\varepsilon_0, \varepsilon_1$ are choice specific preference shocks. The preference shocks have type-I extreme value distribution. The discount factor is δ. The choice-specific deterministic component of the value function is:

$$
\begin{aligned}
V_0(x) &= u_0(x) + \delta \sum_{x' \in X} u_0(x') \pi_1(x'|x, i=0) + \delta^2 \sum_{x' \in X} u_0(x') \pi_2(x'|x, i=0), \qquad (1) \\
V_1(x) &= u_1(x) + \delta \sum_{x' \in X} u_0(x') \pi_1(x'|x, i=1) + \delta^2 \sum_{x' \in X} u_0(x') \pi_2(x'|x, i=1). \qquad (2)
\end{aligned}
$$

where $\pi_t(.)$ is the t year transition probability, and $u_i(.)$ is the instantaneous utility function derived from choice i. This specification uses the assumptions that the time horizon is of three years, and if an individual decides on not attending a screening then she makes that decision for the entire three year period. Here I also neglect the nonzero probability of having to attend further screening one or two years after attending a due screening. Using the distributional assumption, the probability of utilizing preventive care is:

$$
P(x) = \Pr[V_1(x) + \varepsilon_1 \geq V_0(x) + \varepsilon_0] = \frac{\exp[V_1(x)]}{\exp[V_0(x)] + \exp[V_1(x)]}. \qquad (3)
$$

In the empirical analysis I use the normalization of $u_1(x) = 0$. The prerequisites of identification are based on Magnac and Thesmar (2002), and are similar as in the model of Fang and Wang (2010). The model is identified only if there is at least one variable which affects the transition probabilities, but which has no influence on the instantaneous utility of not attending a check-up relative to attending (i.e. no influence $u_0(x) - u_1(x)$). Without this assumption the δ parameter could not be identified. The model then can be estimated with the method of maximum likelihood. In my estimations in section 4.2 I use objective health indicators and the number of GP visits for identifying δ, allowing subjective health to influence the relative utility of screening. I discuss the estimation method in more details in section 4.2.

3 Data

My empirical analysis is based on the British Household Panel Survey (BHPS), waves 1-18. This is an annual survey, which begun in 1991. The survey covers each adult (16+) member of a representative sample of more than 5,000 households from the UK. The focus of the survey is on the social and economic status of the respondents. I restrict the sample to female respondents, aged 50-64. This gives observations for 4.3 thousand individuals, with observation points around 25.5 thousand. Out of these respondents around 3% have died during waves 2-18.

In Table 1 I provide some descriptive statistics of the restricted sample. I present the mean and standard deviation of those variables which I include in the empirical analysis. The education categories are based on the ISCED codes provided in the BHPS data. Secondary education corresponds to having at least lower secondary education but no degree. Higher education corresponds to having at least first degree. As the cutoff between the secondary and higher education categories is not straightforward, in the empirical analysis I use a binary indicator of having secondary or higher education. In the analyzed subsample around 40% of the respondents left schooling before finishing secondary education. This ratio is much less within the younger generations (15% for women aged 20-50). Although the BHPS provides information on the years of schooling of the respondents, I use the categorical indicators of education level as those are less subject to measurement errors. The indicator of good health equals one if the respondent reports excellent or good health status, and the indicator of financial difficulties is one if she reports difficulties or reports "just about getting by." The indicator of working equals one if the respondent reports self employment or paid employment, and is zero otherwise. The chest problem indicator shows chest or breathing problems, asthma, bronchitis, and the stomach problem indicator shows stomach, liver, kidneys or digestive problems. I include the presented health measures in the empirical analysis as those are included in all waves of BHPS, are relatively prevalent conditions, and are reasonably included in the survival probability models. The number of GP visits is measured by a categorical variable ranging from 1 to 5, where 1 corresponds to no GP visits in the previous year, and 5 corresponds to more than ten visits. The dental visits indicator equals one if a respondent reports visiting a dentist during the previous year.

Apart from breast screening, the BHPS provides information also on dental check-ups, eyesight test, X-rays, cholesterol test, blood pressure check, blood test, and cervical smear test. I focus on breast screening as this service type is relatively widely utilized, the potential benefits are well understood, and its effect on survival probability might be observed in the data.

Figure 1 illustrates the utilization of mammography by age. Attending screening is the most likely by the age group 50-70, in line with the NHS recommendations. Overall, 34% of the female respondents in the target age report attending breast screening in the year before the actual survey took place.

The primary aim of breast screening is the early diagnosis of cancer. By itself attending screening cannot help avoiding the development of cancer. As expected, no evidence can be found in the data that attending breast screening would decrease the probability of later being diagnosed with cancer. This analysis is also difficult as having cancer is asked only since the eleventh wave of the survey, and the type of the cancer is not recorded.[3] There is however

[3]It would be reasonable to exclude those respondents from the sample who have been diagnosed with

	mean	standard dev.
age	56.56	4.28
married	0.71	0.45
widow	0.08	0.27
has children	0.88	0.32
white	0.98	0.15
works	0.51	0.50
secondary edu. only	0.52	0.50
higher edu.	0.08	0.27
financial difficulties	0.32	0.42
smoker	0.25	0.43
good health	0.64	0.48
chest problems	0.14	0.35
stomach problems	0.11	0.31
diabetes	0.04	0.19
GP visits	2.63	1.25
dental visits	0.65	0.48
Wales	0.15	0.35
Scotland	0.15	0.36
Northern Ireland	0.11	0.31

Table 1: Descriptive statistics, pooled sample of women aged 50-64

some evidence in the data for the beneficent effect of screening on survival probability. I return to this issue in section 4.2.

4 Empirical analysis

4.1 Reduced form estimation

First I estimate linear probability models of utilization. I estimate pooled cross sectional OLS models. As my main interest here is in the effect of education level, fixed effects models are not suitable, since education level generally does not change within the target age group. Fixed effects models are also not applicable here due to the recommended three-years frequency of screening. In order to avoid omitted variable bias I control for a rich set of individual characteristics.

The basic indicator of utilization equals one if the respondent reports breast screening in the past twelve months. In the alternative and preferred specification I restrict the sample

cancer, since after such a diagnosis the need for health check-ups substantially changes. However, such a restriction cannot be done for the first 10 waves of the survey. In addition, based on waves 11-18 only around 2% of the female respondents aged 50-64 report having cancer.

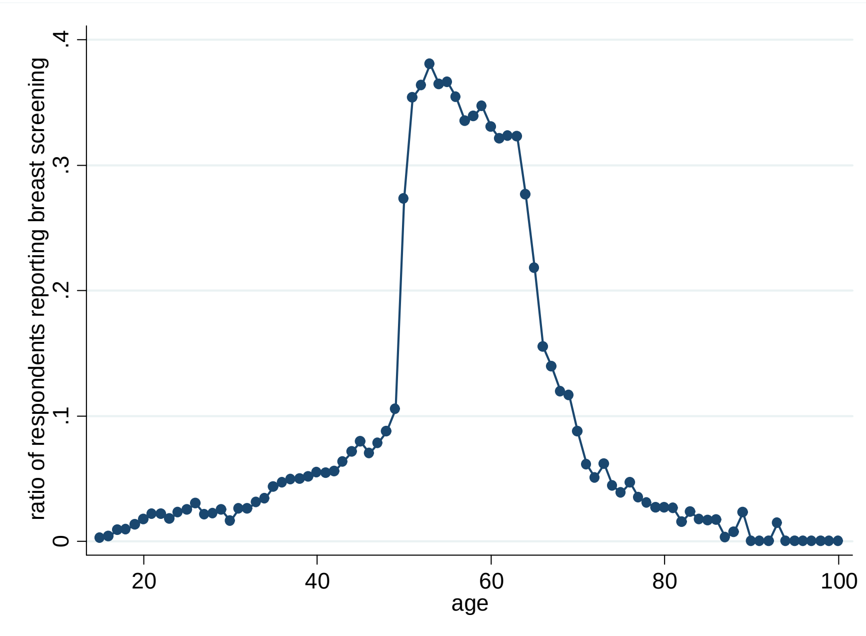

Figure 1: Breast screening attendance by age

to those respondents who have due cancer screening, i.e. who have not attended a screening in the past two years. This restriction corresponds to the institutional settings in the UK.

In Table 2 I report the reduced form estimation results. The standard errors are clustered on the individual level. I start with including only age and education level as regressors. Then I extend the control variables with further socioeconomic and health indicators. In the third specification I also control for GP and dental visits, and for the lagged utilization up to three years before the observation, so as to take into account the institutional set-up of three years frequency of screening, and also to capture some unobservable individual characteristics related to health problems and health care attitudes. The sign pattern of lagged utilization under the third specification indicates the suggested three years frequency of screening.

The weak effect of financial status is reasonable, as more than 95% of the utilizers report that the screening was financed by the NHS. A possible explanation for the positive effect of health (chest problems, subjective health in the third specification) can be that the potential benefits of screening are lower for those who are in worse health status.

Within the relevant age categories, the probability of utilization decreases with age. This might be due to negative experience related to the screening procedure, or to the updated subjective evaluations on the benefits of screening. This effect disappears once the sample is restricted to those who have not attended a screening in the past two years. These differences also highlight that focusing only on the basic indicator of attendance can be misleading. Married and white women and those who have children are estimated to be more likely to attend screening, although some of the coefficients are insignificant. Attending a screening is more likely in England than in the rest of the UK, holding the other factors fixed. The indicators of health behavior have the expected effect: smoking decreases, whereas reporting a dental visit and higher number of GP visits increase the likelihood of attending a screening.

An education gradient can also be observed: those with secondary or higher education are ceteris paribus more likely to attend screening. This effect is estimated to be stronger if the screening is due. However, the estimated partial effect of education level becomes insignificant it the indicators of health care attitudes are controlled for. This suggests that the education gradient is not specific to breast screening, but it is a general phenomenon of preventive care, or more generally of health care utilization.

The explanatory power of the regression models is very weak. The included characteristics can explain only little part of the within and between individual variation in utilization.

4.2 Structural estimation

I estimate the model described in section 2. The main parameters of interest are the discount factor and the effect of education level on the relative utility derived from not attending a due screening. I apply a two-step estimation method. In the first step I estimate the transition probabilities, and in the second step I estimate the discount rate and the parameters of the utility function. I assume the current utility to be a linear function of the observable characteristics. I also assume that the only uncertainty is survival. Apart from age I treat the other observable characteristics as fixed throughout time. This is reasonable e.g. for education level and gender, but might be problematic for employment or health status. However, as one can assume that breast screening does not influence the employment status or the perceived health status in the short run, this simplifying assumption is innocuous. In addition, as in the short run the effects of attending a mammography are small, it is not possible to arrive at reasonable estimates by extending the model to allow mammography to influence health or employment status as well. Thus I consider the screening to have the sole purpose of increasing longevity through the early diagnosis of breast cancer. I restrict the estimating sample to females aged 50-64 who have due breast screening.

As the first step of the estimation, I estimate logit models of one- and two-year survival, and predict the survival probability with and without breast screening for each individual in the sample. Apart from attending the due screening, I include age, working status,

	Screening - basic indicator			Due screening		
age	-0.002***	-0.002***	-0.007***	0.002*	0.002	0.003*
	[2.70]	[2.61]	[7.52]	[1.64]	[1.10]	[1.86]
secondary or higher edu.	0.021***	0.014	0.008	0.054***	0.037**	0.021
	[2.72]	[1.52]	[0.99]	[4.09]	[2.47]	[1.41]
work		0.000	-0.002		0.011	0.014
		[0.04]	[0.22]		[0.74]	[0.95]
married		0.044***	0.036***		0.089***	0.085***
		[4.07]	[3.71]		[5.67]	[5.55]
widow		0.019	0.025		0.059**	0.058**
		[1.14]	[1.54]		[2.19]	[2.20]
has child		0.020	0.008		0.021	0.018
		[1.51]	[0.63]		[1.05]	[0.88]
white		0.024	0.004		0.066*	0.069*
		[0.79]	[0.17]		[1.68]	[1.77]
financial difficulties		-0.002	0.006		-0.019	-0.018
		[0.28]	[0.67]		[1.48]	[1.42]
smoker		-0.030***	-0.013		-0.067***	-0.051***
		[3.04]	[1.34]		[4.34]	[3.42]
chest problems		0.020*	0.011		0.024	0.014
		[1.71]	[0.94]		[1.28]	[0.72]
stomach problems		0.010	-0.004		0.007	-0.012
		[0.78]	[0.32]		[0.33]	[0.58]
diabetes		0.010	0.003		0.017	0.011
		[0.48]	[0.17]		[0.46]	[0.29]
Wales		-0.009	-0.006		-0.025	-0.025
		[0.79]	[0.53]		[1.36]	[1.39]
Scotland		-0.012	-0.013		-0.054***	-0.050***
		[1.07]	[1.27]		[3.19]	[3.03]
Northern Ireland		-0.006	-0.008		-0.040	-0.069
		[0.10]	[0.12]		[0.42]	[0.70]
good health		-0.020**	0.017*		0.006	0.043***
		[2.31]	[1.80]		[0.42]	[2.99]
GP visits			0.027***			0.036***
			[7.33]			[6.42]
dental visits			0.039***			0.086***
			[4.49]			[6.47]
utilization, previous year			0.010			
			[1.14]			
utilization, 2 ys before			-0.019**			
			[2.25]			
utilization, 3 ys before			0.290***			
			[30.54]			
Constant	0.437***	0.409***	0.492***	0.193***	0.102	-0.117
	[10.36]	[6.61]	[7.97]	[2.94]	[1.13]	[1.28]
Observations	25,226	19,844	15,091	9,687	8,004	7,996
R-squared	0.00	0.00	0.09	0.00	0.02	0.03

t statistics in brackets based on cluster standard errors
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2: Reduced form estimation results of utilization

smoking, reporting good health, health problems with chest or breathing and with stomach or digestion, having diabetes, and the indicator of the number of GP visits in the previous year. I include these observables as these can reasonably affect the survival probability, and are significant in the logit models. The number of GP visits and the three objective health indicators are excluded from the second stage model of instantaneous utility, as I assume that instead of the objective measures the reported subjective health influences the utility difference between attending and not attending a breast screening. Although the number of GP visits can also indicate health care attitudes, I assume that it rather captures health problems. The exclusion restrictions are needed for the identification of the discount factor. In section 4.3 I present some robustness checks on the excluded variables.

I report the estimated logit coefficients, average marginal effects, and the average predicted survival probabilities with and without mammography in Table 3. Breast screening is estimated to significantly increase the survival probability. However, as the marginal effects and predicted probabilities show, the magnitude of this observed positive short run effect is relatively small. As the potential benefits of breast screening on survival probability are likely to be in the long run, these estimates cannot capture the total benefits of screening. On the other hand, omitted variables (unobserved health behaviors related to screening) might cause upward bias in the estimated effects. Although I estimate here the short run effects of a single screening, these estimates can still capture the effect of regular attendance on screening. The data indicate that if a woman in the target age category did not attend a due screening three years before then her probability of attending a screening this year is on average 20.5%. However, if she attended the last due screening then the current probability of attendance is 62.4%. Thus observing participation on a due screening generally implies regular attendance.[4]

The second step is the maximum likelihood estimation of the utilization model. I assume that the following indicators influence the relative disutility of attending a due breast screening: age, secondary or higher education level, being married, reporting good health, smoking, and living in Scotland, Wales, or Northern Ireland. So as to reduce the noise in the estimation results, I exclude those observable characteristics which could be considered as influential in the relative disutility of screening, but are estimated to have a coefficient with a high p-value (e.g. labor force status). In section 4.3 I also present some robustness checks with respect to the included variables in the model of relative utility.

In the basic specification I estimate a single parameter of discount factor, whereas in

[4]Nonrandom attrition can bias the estimation results. This bias is present if attrition (due to factors other than death) is related to unobservables which influence the survival probability. The attrition and its explanatory factors in BHPS are discussed in details by Uhrig (2008).

	Coefficients		Average marginal effects	
	1-yr survival	2-yrs survival	1-yr survival	2-yrs survival
screening	0.934**	0.524*	0.0046***	0.0057**
	[2.37]	[1.95]	[2.86]	[2.04]
age	-0.106***	-0.099***	-0.0006***	-0.0012***
	[2.88]	[3.24]	[2.66]	[3.04]
work	1.057**	0.766***	0.0050***	0.0081***
	[2.25]	[2.60]	[2.74]	[2.82]
smoker	-0.252	-0.496*	-0.0016	-0.0064*
	[0.82]	[1.78]	[0.79]	[1.63]
good health	0.765*	0.577*	0.0042**	0.0066*
	[1.84]	[1.88]	[1.96]	[1.92]
GP visits (1-5)	-0.309**	-0.305**	-0.0019**	-0.0037**
	[2.21]	[2.43]	[2.11]	[2.35]
chest problems	-0.539	-0.623**	-0.0036	-0.0086*
	[1.64]	[2.08]	[1.46]	[1.80]
stomach problems	-0.714**	-0.599*	-0.0052*	-0.0086*
	[2.07]	[1.92]	[1.69]	[1.63]
diabetes	-0.366	-0.414	-0.0025	-0.0059
	[0.75]	[0.84]	[0.65]	[0.72]
constant	11.561***	10.675***		
	[5.21]	[5.70]		
Observations	7,951	6,897		
Pseudo R^2	0.15	0.13		

* significant at 10%; ** significant at 5%; *** significant at 1%
t statistics in brackets based on cluster standard errors

Average predicted survival probabilities

	1-yr survival	2-yrs survival
No screening	99.22%	98.52%
With screening	99.69%	99.11%

Table 3: Logit model estimation results of survival

the extended specification I allow the discount factor to differ between the two education categories. The estimated parameters of the linear utility function and of the discount factor are reported in Table 4. The first column corresponds to the basic specification, and the second column shows the results with heterogeneous discount factor. The standard errors are clustered on the individual level, but do not take into account the two step estimation method.[5] Due to the small variation in the observed survival, and to the complex setup of the

[5]Applying the Murphy-Topel correction to the standard errors has little effect. The correction is done following Greene (2003), p. 510. The difference between the original and the corrected standard errors are of the magnitude of 10^{-6}, thus the correction does not influence the significance of the parameters.

likelihood function, estimating a full information maximum likelihood model of utilization does not provide reliable results. Therefore the two-step estimation procedure is preferred here.

The estimated coefficients of the linear utility function indicate that the relative disutility attached to attendance decreases with age and being married. The relative disutility is higher for women living outside England, and for those who report smoking.[6] The results also suggest that the education differences in mammography decisions are likely to be driven by the different disutility attached to mammography. Those who have secondary or higher education level are estimated to derive less utility from not attending a due breast screening. This difference is significant at the 1% or 5% significance level, depending on allowing for heterogeneous discount factor. As in Fletcher and Frisvold (2009), these differences along education might be caused by different occupations and different access to care, among others. The average estimated relative disutility of attendance is positive, indicating that mammography has some non-pecuniary costs (e.g. discomfort, time costs).

The estimated discount factor is larger than one. This suggests that individuals are forward looking when making decisions on breast screening, and put higher weight on the future benefits than on the current costs. The high discount factor can also indicate that people overestimate the potential benefits of mammography. There is some empirical evidence in the related literature that the discount rate in health decisions is negative, and discounting health and monetary outcomes might be different. For a discussion on this issue, see e.g. Ortendahl and Fries (2006). I find no evidence that the discount factor would significantly differ between the two education categories, thus the differences in utilization are not driven by different time preferences.

In order to obtain more insights into the driving factors of the large estimated discount factor, I check what happens if I set the discount factor to the often applied 0.9 level. I then estimate the utility and survival function parameters in one step with using this restriction on the discount factor. The variables included in the survival and relative utility functions are the same as before. For the sake of estimability, I assume here that the one-year mortality hazard is the same during the two years after the decision on screening. The estimated coefficient of screening in the logit model of one-year survival becomes 2.43, implying a marginal effect of 0.47. Thus if we assume that the discount rate is 10% then this implies that the women in the target age category consider missing a due breast screening to decrease the one-year survival probability by 47%. This again suggests subjective overestimation of

[6] The strong ceteris paribus effect of living in Scotland could already be seen in the reduced form estimation results (Table 2). Investigating the driving factors behind these regional differences is out of the scope of this paper and remains for further research.

Disutility parameters $(u_0(.) - u_1(.))$		
age	-0.008***	-0.008***
	[17.10]	[5.92]
secondary or higher education	-0.184***	-0.179**
	[2.88]	[2.46]
married	-0.394***	-0.395***
	[6.24]	[5.66]
good health	-0.083	-0.084
	[1.44]	[1.40]
smoker	0.353***	0.354***
	[5.04]	[4.81]
Scotland	0.230***	0.231***
	[2.62]	[2.90]
Wales	0.100	0.100
	[1.22]	[0.98]
Northern Ireland	0.164*	0.164*
	[1.89]	[1.79]
Constant	1.456***	1.449***
	[17.59]	[22.78]
Discount factor		
δ	2.012***	1.954**
	[3.45]	[2.52]
$\delta\cdot$ secondary or higher edu.		0.228
		[0.20]

* significant at 10%; ** significant at 5%; *** significant at 1%
t statistics in brackets based on cluster standard errors

Table 4: Maximum likelihood estimation results

the benefits of screening.

4.3 Specification checks

As a first robustness check I replace the binary indicator of education with the years of schooling. I censor the reported years of schooling at 25. The so generated schooling variable has mean of 13.2 and standard deviation of 3.8 in the subsample of females aged $50-64$. In this specification the coefficient of the years of schooling is -0.011 (with t-statistics of 1.66), and the discount factor is 1.863 (with t-statistics of 2.68). These results confirm that the disutility of screening decreases with education level, and that the discount factor is close to two.

In the following I conduct a set of robustness checks so as to test how sensitive the benchmark maximum likelihood estimation results are to the modelling assumptions. Under these specification checks I estimate a single discount factor, i.e. I do not allow for heterogeneity between the education categories. First, I assume that living in Wales and the subjective health indicator do not influence the instantaneous relative utility of breast screening. I exclude these variables since these were insignificant in the benchmark specification. Under the second specification I include the binary indicator of visiting a dentist in the model of relative disutility attached to mammography. Visiting a dentist can capture general attitudes towards preventive care, without having influence on the survival probability. I do not include this variable in the benchmark specification since I am interested in the overall effect of education, which can include general preventive care attitudes. Next, I take into account that some respondents have to attend a repeated screening within the next two years, and also that some respondents who do not attend a due screening just postpone it. In this specification I use the observed ratios of repeated and postponed screening: 26 and 18% of the respondents attend a screening one and two years after attending a due breast screening, and 25 and 22% attend a screening one and two year after they miss a due screening. I assume here that the probabilities of repeated and postponed screening are exogenously determined and the same for everyone. These assumptions are realistic for the probability of repeated screening, but simplifying for the probability of postponed screening. Finally, I repeat the benchmark estimations with the assumption that the decision makers take into consideration only two years, instead of three. This specification check can provide some insight into the importance of the assumptions about time horizon.

I present the estimated coefficients of interest in Table 5. Apart from the second specification, the negative effect of secondary or higher education level on the instantaneous disutility of screening is a robust finding, and its estimated magnitude is also robust across the different specifications. Once dental care is included as an explanatory variable then the coefficient of education becomes insignificant, and smaller in absolute value. This indicates that more educated women attach smaller disutility to breast screening because of generally more positive attitudes towards health care. Thus the education gradient is not a unique feature of mammography.

The estimated discount factor is qualitatively robust to the alternative specifications with three-year time horizon. It is lower but still above one if subjective health and living in Wales are not included among the influencing factors of relative utility. However, if two-year horizon is assumed then the discount factor can be estimated only with large standard error, and its estimated magnitude more than doubles. The higher estimated discount factor is reasonable as the one-year benefits of mammography in terms of survival probability are minor, thus this model estimates that women put a large emphasis on these small potential benefits. This result also suggests that the three-year model is likely to overestimate the discount factor, as in reality more than three years of benefits might be taken into account when making a decision on screening.

As an additional specification check I check the importance of the exclusion restrictions. If there are no exclusion restrictions then the model can be still estimated with ML, but the identification is based on the functional form. As reported in the last part of Table 5, the education coefficient is still robust to this specification, but the estimated discount factor becomes negative and insignificant. Thus the previously documented relative robustness of the discount factor holds only if that is identified not only by functional form, but also with the help of exclusion restrictions. On the other hand, if the binary indicator of smoking is also excluded from the relative utility part of the model then the discount factor remains high, but the education coefficient diminishes and becomes insignificant, indicating that it is important to control for this observable behavior.

Disutility parameters $(u_0(.) - u_1(.))$	Wales and subjective health excl.	Dental care included	Repeated and postponed screening	2-year decision	No exclusion restrictions	Smoking excluded
secondary or	-0.191***	-0.099	-0.216***	-0.181***	-0.165**	-0.017
higher education	[2.99]	[1.49]	[2.97]	[2.98]	[2.04]	[1.46]
Discount factor						
δ	1.574*	1.922***	2.201***	5.309	-0.624	1.652*
	[1.93]	[3.39]	[8.39]	[1.56]	[1.51]	[1.69]

* significant at 10%; ** significant at 5%; *** significant at 1%

t statistics in brackets based on cluster standard errors

Table 5: Robustness checks: maximum likelihood estimation results - selected parameters

I also estimate a modified version of the utilization model, so as to get further insights into the underlying process of decision making and to relax the assumption of short time horizon. In this alternative model I use the age pattern of invitation to mammography screening. Before 2004 only those aged between 50-64 were invited. This implies that in the corresponding BHPS waves if a woman aged 62-64 had a due screening then she could make the decision on utilization assuming that she would not attend further screening in the future. I assume that conditional on this utilization decision the one-year survival probability remains constant, the planning horizon is 50 years, and apart from age, the observed individual specific characteristics are expected to remain constant throughout time. The only uncertainty is survival to the next period. Thus the value functions become:

$$V_0\left(x^0\right) = u_0\left(x^0\right)+\sum_{t=1}^{50}\delta^t\left(S\left(x^0,\ i=0\right)\right)^t u_0\left(x^t\right), \tag{4}$$

$$V_1\left(x^0\right) = u_1\left(x^0\right)+\sum_{t=1}^{50}\delta^t\left(S\left(x^0,\ i=1\right)\right)^t u_0\left(x^t\right), \tag{5}$$

where $S(.)$ denotes the one-year survival probability,[7] and x^t is the vector of characteristics at time t. Based on these value functions the utilization model can be estimated with the method of maximum likelihood. I normalize $u_1(x)=0$, estimate the probability of survival with logit model, and assume that the utility function is linear. I use the same set of regressors in the logit model of survival as in section 4.2. However, due to the small estimating sample it is not possible to estimate a rich set of parameters in the empirical function of relative utility. Thus I include only age, the binary indicator of secondary or higher education level, and smoking, which can capture differences in health behaviors.[8] I present the estimated parameters of this model in Table 6.

Again, there is evidence that those with higher education attach lower disutility to mammography, and this difference is significant at the 5% significance level. The estimated discount factor is lower than the benchmark estimate, however, it can be estimated only with a large standard error. The decreased magnitude can be partly due to the age restriction of this alternative specification, implying that the discount rate of women aged 62-64 is higher than of the age group 50-61. A more plausible explanation is based on the different modeling assumptions. In this alternative specification the positive effects of screening are overestimated as I assume that the one-period beneficial effect remains the same throughout the next 50 years. This is an unrealistic assumption, but based on the data it is not possible to reliably estimate the long-run benefits of mammography. Once I impose these high hypothetical benefits of screening, the discount factor becomes lower than before. Thus it again implies that the previous high estimates of the discount factor are due to the high subjective evaluations on the benefits of mammography.

[7] The difference from the $\pi(.)$ function of equations (1) and (2) is that here $S(.)$ is constant throughout time conditional on screening attendance, i.e. does not depend on age.

[8] The coefficient estimates are robust to including the same set of regressors as before, however, in this extended model not all of the standard errors can be estimated.

Disutility parameters $(u_0(.) - u_1(.))$	
age	0.072***
	[40.46]
secondary or higher education	-0.422***
	[2.24]
smoker	0.648***
	[2.59]
constant	-3.700**
	[41.66]
Discount factor	
δ	0.440
	[0.63]

* significant at 10%; ** significant at 5%; *** significant at 1%
t statistics in brackets based on cluster standard errors

Table 6: Maximum likelihood estimation results, alternative specification for aged 62-64

5 Concluding remarks

In this paper I analyze mammography attendance among women aged 50-64 in the UK. My aims are to estimate the discount factor implied by mammography decisions, and to analyze the education differences in utilization. The empirical analysis is based on the 18 waves of the British Household Panel Survey.

Reduced form estimation results suggest that the observed education gradient is mainly due to differences in health behaviors and health care attitudes, and not due to different attitudes towards breast screening in particular. Estimating a semi-parametric structural model reveals that although there are differences in the disutility of breast screening along the education level, there is no such difference in the estimated discount factor. Thus these results suggest that if there are differences in the utilization of preventive services across different education groups, those are rather the consequences of attitudes towards and conceptions about these services, and not of the potentially different time preferences.

The estimated one-year discount factor is around two. This result suggests that women might overestimate the potential benefits of breast screening, which leads to over-utilization. However, this estimation result can also imply that the benefits of mammography are realized in the long run, and women take into consideration those long term benefits when making a decision on attending a screening. Specification checks suggest that both of these mechanisms contribute to the high estimated discount factor.

The results of this paper are based on a set of simplifying assumptions, which are necessary due to data limitations and for the sake of the estimability of the empirical models. Among others, I assume that the only uncertainty is survival, and that the decision makers have short time horizon. Acknowledging these limitations, this analysis can be considered as a simple step towards getting more insights into the demand for breast screening.

References

Agency for Healthcare Research and Quality. 2009. "Screening for Breast Cancer: Systematic Evidence Review Update for the U. S. Preventive Services Task Force." Evidence Review Update, No. 74. *AHRQ Publication*, No. 10-05142-EF-1.

Albano, J. D. et al. 2007. "Cancer Mortality in the United States by Education Level and Race." *Journal of the National Cancer Institute*, 99(18): 1384-1394.

Ayyagari, P. 2007. "Do Health Shocks Affect Preventive Behavior?" Department of Economics, Duke University.

Cancer Research UK. 2012.
http://cancerhelp.cancerresearchuk.org/type/breast-cancer/about/screening/mammograms-in-breast-screening,
http://info.cancerresearchuk.org/cancerstats/types/breast/screening/history/

Cutler, D. M., and A. Lleras-Muney. 2010. "Understanding differences in health behaviors by education." *Journal of Health Economics*, 29: 1–28.

Fang, H. and Y. Wang. 2010. "Estimating Dynamic Discrete Choice Models with Hyperbolic Discounting, with an Application to Mammography Decisions." *NBER Working Paper*, No. 16438.

Fletcher, J. M. and D. E. Frisvold. 2009. "Higher Education and Health Investments: Does More Schooling Affect Preventive Health Care Use?" *Journal of Human Capital*, 3(2): 144-176.

Fuchs, V. R. 1982. "Time Preference and Health: An Exploratory Study." In: *Economic Aspects of Health*, ed. V. R. Fuchs. University of Chicago Press.

Gotzsche, P. C., and O. Olsen. 2000. "Is screening for breast cancer with mammography justifiable?" *Lancet*, 355: 129–134.

Greene, W. H. 2003. *Econometric Analysis.* Fifth edition. Prentice Hall, Pearson Education International.

Grossman, M. 1972. "On the concept of health capital and the demand for health." *Journal of Political Economy*, 80: 223-255.

Hofer, T. P., and S. J. Katz. 1996. "Healthy Behaviors among Women in the United States and Ontario: The Effect on Use of Preventive Care." *American Journal of Public Health*, 86 (12): 1755-1759.

Hotz, V. J., and R. A. Miller. 1993. "Conditional Choice Probabilities and the Estimation of Dynamic Models." *The Review of Economic Studies*, 60(3): 497-529.

Hussain, S. K. et al. 2007. "Influence of education level on cancer survival in Sweden." *Annals of Oncology*, 19(1): 156-162.

Jusot, F., Z. Or, and N. Sirven. 2011. "Variations in preventive care utilisation in Europe." *European Journal of Ageing*, forthcoming.

Lee, J. R-J., and V. G. Vogel. 1995. "Who Uses Screening Mammography Regularly?" *Cancer Epidemiology, Biomarkers and Prevention*, 4: 901-906.

Magnac, T., and D. Thesmar. 2002. "Identifying Dynamic Discrete Decision Processes." *Econometrica*, 70(2): 801-816.

Maurer, J. 2009. "Who has a clue to preventing the flu? Unravelling supply and demand effects on the take-up of influenza vaccinations." *Journal of Health Economics,* 28: 704–717.

Maxwell, C. J. et al. 1997. "Factors important in promoting mammography screening among Canadian women." *Canadian Journal of Public Economics*, 88(5): 346-350.

Moser, K., J. Patnick, and V. Beral. 2009. "Inequalities in reported use of breast and cervical screening in Great Britain: analysis of cross sectional survey data." *BMJ: British Medical Journal*, 338: b2025.

Ortendahl, M. and J. F. Fries. 2006. "A low tension between individual and societal time aspects in health improved outcomes." *Journal of Clinical Epidemiology*, 59: 1222-1227.

Phelps, C. E. 1978. "Illness Prevention and Medical Insurance." *The Journal of Human Resources*, 13 (Supplement): 183-207.

Picone, G., M. Uribe, and R. M. Wilson. 1998. "The effect of uncertainty on the demand for medical care, health capital and wealth." *Journal of Health Economics,* 17: 171–185.

Pol, M van der. 2011. "Health, education and time preference." *Health Economics*, 20: 917-929.

Uhrig, S. C. N. 2008. "The Nature and Causes of Attrition in the British Household Panel Survey." *ISER Working Paper Series*, No. 2008-05.