The Impact of Health Plan Type on the Rate of Preventive Care and the Probability of Diagnosing Health Conditions

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Abstract

This paper tests whether health maintenance organization (HMO) coverage leads to better preventive care for middle-aged and near-elderly adults. Seven common types of preventive care tests and three types of common chronic diseases whose diagnosis is strongly dependent on screening were analyzed. I control for selection into HMOs with a novel quasi-experiment: turnover in insurance contracts at the firm level creates exogenous variation in plan type. Rates of testing are slightly higher for some types of cancer screenings and about the same for other types of screening after controlling for selection. Furthermore, the paper explores self-awareness of several common health conditions: hypertension, hypercholesterolemia, and diabetes. These measures are constructed using a biological screening done by the Health and Retirement Survey. The probability of having one of these conditions and being unaware of it is about the same between members with HMO and non-HMO coverage.

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1 Introduction

Over the last several decades, healthcare providers have been encouraged to increase the use of preventive health services, such as screening tests and counseling services, in order to improve clinical outcomes for patients.[1] Several types of preventive care tests, including cancer screening and cholesterol testing, have been shown to improve health and decrease mortality (Maciosek et al., 2006). Proponents of preventive care testing emphasize that these types of tests can help screen for problems early and potentially lead to faster diagnosis and treatment. Although this seems plausible, some researchers have questioned whether or not this idea holds true for all patients. In fact, most forms of preventive measures may not be cost-effective for all types of patients.[2] A large meta-analysis conducted on the value of preventive care services found that in order for preventive care to be cost-efficient, it should primarily be targeted towards populations at high-risk for the underlying condition being screened or prevented (Cohen et al., 2008). One such population is the middle-aged and near-elderly subgroups, who naturally begin to develop a risk for certain diseases as they age. While there is a general consensus that older adults are a high-risk population, not every adult in this sub-population receives the amount of screening recommended by the U.S. Preventive Care Task Force (2012). Researchers and policy makers have identified health plan benefit type, including the HMO structure, as an important potential contributing factor in whether an adult undergoes appropriate preventive care screening tests.

[1] These recommendations are provided by various experts and medical teams, such as the U.S. Preventive Services Task Force, which seeks to use evidence-based medicine to outline which type of preventive testing is most worthwhile.

[2] For example, Russell (2007) found preventive care testing may be too costly if the test needs to be administered to a large population in order to reach a small population that benefits from the test.

There is interest in understanding HMO plans because they are an easy classification to study with a potentially large impact on healthcare usage and outcomes. Aspects of the HMO like the primary care physician gatekeeper, low-copay, and narrow network are clear differentiators. Differences in outcomes seen at the plan level can spark further study into specific causal pathways, and policy-makers can encourage the use of network designs aspects they see as beneficial, as was done with the Health Maintenance Organization Act of 1973. There have been several papers examining the topic of health plan type and preventive care.[3] A survey paper by Miller and Luft (2002) summarizes these results, "Findings on prevention (mostly cancer screening) were consistently favorable to HMOs." These papers attempt to control for selection using observed demographics such as health status or age. However, if there is unobserved selection into HMO plan type, then these results are likely biased. Selection is a concern because when individuals choose their health plan they may take into account their preference for preventive care. If HMOs offer better incentives to use preventive care, this could attract individuals who would be more likely to use preventive care. This adverse selection would lead to a spurious correlation between HMOs and preventive care. [4]

There are only a handful of studies that control for selection using techniques other than selection on observables. Wells et al. (1992) considered three firms that changed to a PPO option from a less restrictive plan type and found no long-term changes in usage. Rizzo (2005) used HMO market penetration to instrument for individual HMO enrollment and found some increases in preventive care. However, it is possible that HMO expansion was due to changing market demographics and desires for preventive care that might bias the results of the instrument. Indeed, HMO market penetration

[3]Tye et al. (2004) found individuals in HMOs were more likely to receive mammograms. Kenkel (1994) found HMO members underwent less breast exams and PAP smears. On the other hand, Wang and Pauly (2003) found that HMOs increased the use of mammograms, pap smears, and blood pressure measurements in the near-elderly. Weinick and Beauregard (1997) found preferred provider organization (PPO) plans have increased the use of blood pressure checks, PAP smears, and breast exams to match HMO rates as a result of HMO competition.

[4]Indeed, there is already some evidence that shows HMO enrollees differ from non-HMO enrollees. Frank et al. (2000) developed and tested a theory that showed HMOs attract healthier than average patient populations, a practice called 'cream skimming.'

has been associated with increased use of preventive care among non-HMO plans, leaving open the possibility that HMO expansion was caused by factors correlated with both HMO expansion and an increased desire for preventive care.[5]

This study builds on prior studies by utilizing observable controls and a quasi-experiment to control for selection. The study's data comes from the 1996 to 2010 waves of the HRS which contains information on respondents use of preventive care. In the first part of the study, I use a quasi-experiment in order to compare the frequency of undergoing several preventive care tests between individuals enrolled in an HMO versus a non-HMO plan. To control for selection into HMO or non-HMO plans, I use the variation in HMO and non-HMO status that comes from a firm that offers only one choice of insurance and later switches from offering HMO coverage to a non-HMO plan or vice-versa during an employee's tenure. In these instances, the treatment, HMO status, is exogenous because it is unlikely that a change in an employer's health insurance arrangement would reflect a change in preferences for preventive care of a particular individual. A difference-in-differences empirical model is then run on two different sets of treatment and control sample groups. The first treatment group is made of enrollees who had a non-HMO plan and were switched through their employer to an HMO plan. The control group is the set of individuals enrolled in non-HMO plans whose employers did not switch insurance types. This comprises the first group. The second group is composed of a treatment cohort of individuals enrolled in HMO plans whose employers switched their plan offering to a non-HMO. In this case, the control group is composed of individuals enrolled in an HMO who were not switched. I use these different sample groups to run two different sets of regressions of preventive care on HMO status.

In the second half of the study, I then examine the rate of self-awareness versus actual presence of undiagnosed diseases in the HMO and non-HMO group using the

[5]See Baker et al. (2010); Bokhari (2009); Phillips et al. (1998); Glied (2000); Mukamel et al. (2001) Another possibility is that HMO expansion caused non-HMO plans to increase preventive care useage through competition. In that case, the instrument would suffer from contamination. Thus, only the intention to treat effect can be identified.

responses to the personal health screening questions asked to participants and biological screening tests done on participants in the HRS. I look at individuals' responses to whether or not they believed they had diabetes, hypercholesteremia, or high blood pressure and compared their answers to three biological health measures, elevated blood glucose levels, cholesterol levels, and blood pressure readings. Using these responses, I can correlate an individual's self-awareness of health to HMO or non-HMO status. Self-awareness can be thought of as an output of screening. Individuals can only be fully aware that they have diabetes, hypercholesteremia, or high blood pressure if they have been screened for it. Therefore, I view screening and self-awareness of disease as complementary measures. The advantage to looking at self-awareness is that it does not penalize those who do not screen patients who are unlikely to benefit from screening.

Using employer health plan turnover as the source of health plan variation has potential pitfalls. Changes in the average demographic characteristics of the firm may impact health plan offerings. If there is correlation between firm level demographics and sampled individual demographics that affect the propensity to use preventive care, then the source of variation may be contaminated. I minimize this possibility by using a rich set of characteristics, including: age bins, the interaction of the age bins and HMO status where indicated, marital status, race, gender, health, industry code, occupation code, household earnings, census division, health, and time fixed effects. One caveat is that employees whose job choice is elastic to contract-type may leave the firm before being sampled in the HRS. Therefore, the sample of compliers, those who stayed with the firm after the change in insurance contracts, may have different characteristics and responses to HMO insurance than the non-compliers.

Based on the data, my findings are that middle-aged individuals in an HMO are slightly more likely to receive preventive care, especially cancer screenings, than those in a non-HMO. However, this difference decreases as enrollees age, until the rates of testing between HMO and non-HMO plan individuals are nearly identical. I also find that individual self-awareness regarding certain health concerns that are more likely

to arise as individuals age (elevated cholesterol, blood sugar, and blood pressure) are essentially the same for all individuals regardless of health insurance type. This could indicate that HMO providers do not necessarily offer better patient education regarding these health concerns or could stem from the fact that older patients not seem to receive more preventive care in HMOs.

The rest of the paper is organized as follows: Section 2 describes the data, Section 3 lays out the justification for the econometric model, Section 4 interprets the results, and Section 5 summarizes the contribution of the paper and objectives for future research.

2 Data

The data come from the Health and Retirement Study (HRS), an ongoing longitudinal biennial survey of older Americans. The survey is administered by the University of Michigan and funded by the National Institute of Aging. The total sample size of the first wave, in 1992, was 12,654 respondents, with an initial response rate of 82%. The HRS averages about a 90% living person response rate at follow-up.[6] Participants were drawn from those born in 1931-1941 and their spouses. New cohorts were added later. This study also uses the Biomarker file, a panel survey of various biochemical, metabolic, and endocrine measures collected in face to face interviews. The HRS questions are extensive and delve into assets, income,[7] employment, health insurance characteristics, health characteristics, physical and biological exams. Therefore, the data set contains the components necessary to answer the questions posed in the introduction.

I impose several restrictions on the data for the purpose of this study. First, individuals must be 45 or older and less than 65. The cutoff, age 65, was chosen because at that age individuals have access to Medicare in addition to private insurance. The HRS contains few individuals younger than 45, so inference at ages younger than 45 is unlikely to be fruitful. Those with non-responses for control variables are eliminated.

[6]For more information see the HRS website: http://hrsonline.isr.umich.edu/index.php?p=intro
[7]All monetary values were deflated to 2010 values using the Consumer Price Index.

Additionally, individuals with wealth less than the 1st percentile or above the 99th percentile are dropped. Individuals must be working at a firm that offers only one insurance choice and be enrolled in that insurance plan. This is because the estimator relies on firm plan offerings forcing the individual's choice of health plan. Military and federal government workers and individuals insured through government programs such as Medicare or Medicaid and those who buy their insurance on the individual market are excluded.

When conducting the difference in differences analysis, two groups are used who meet different inclusion criteria. The first inclusion criteria used for both groups is a restriction to those with only one insurance option at their workplace. For the first group, the non-HMO to HMO group, employees must have either non-HMO coverage for the entirety of the job tenure or non-HMO coverage at the beginning of employment and later a switch to HMO coverage at the behest of the employer. For the HMO to non-HMO group, the inclusion criteria is similar (i.e. those with HMO coverage for the entire job tenure or HMO coverage at the beginning and a switch to non-HMO coverage because of the employer). The combined number of individuals in each of these groups is 18,901, 10,926 in the non-HMO to HMO group and 7,975 in the HMO to non-HMO group.

Insurance type is constructed by combining a series of questions in the HRS about aspects of the insurance contract. This study defines an individual as a member of an HMO plan if they report having an HMO plan and a list of physicians they must use. The constructed variable equals one if the person has an HMO and equals zero if they do not. In the data, about one third of those with private health insurance through an employer who reported their contract-type had an HMO contract. Other insurance questions in the HRS can be mapped to three other common types of insurance: preferred provider organization and point-of-service. In the analysis, these three types are grouped into non-HMO. This study does not use data prior to 1996 because no questions about HMO plans were asked before 1996.

As described in the Introduction, I also construct another set measures of preventive

care that do not directly look at utilization but instead examine self-knowledge of an individual's underlying health. I construct this measure using several responses from the HRS. First, I look at responses to questions regarding whether an individual has been told by a doctor that they had hypertension, diabetes, or high cholesterol. What I call their self-awareness. I then compare their responses to the results of tests administered by the HRS surveyor which I have condensed into indicators for likely having the conditions hypertension, diabetes, or high cholesterol. I infer the respondee had high blood pressure if their average systolic was above 140 and their average diastolic was above 90.[8] Surveyors also took blood samples used to measure blood cholesterol. I infer someone had high cholesterol if their total cholesterol was above 240 or if they were male with a high density lipid (HDL) below 40 or they were female with an HDL below 50.[9] Surveyors also measured a person's hemoglobin A1C level, the gold standard test diagnosing diabetes. I infer a person had diabetes if their A1C was above 6.5.[10] For the purposes of this study I label these three tests biological screens.

In the final step, I combine respondent self-awareness of health with the additional information from the biological screens in the HRS. With this combined information, I construct three measures of "missed diagnosis." These variables equal 1 when an individual did not report a doctor telling them they had one of the underlying conditions, but the biological screens showed they did have the condition. A value of 0 is given when either the individual does report a doctor telling them they have the underlying condition, or they report a doctor did not tell them they had the underlying condition and the tests from the HRS confirm those reports. These measures are labelled Hypertension miss, Diabetes miss and High cholesterol miss. For more on the construction of these variables, as well as information on the acceptability of the criteria used in the biological screens, see Appendix B.

[8]Guidelines taken from Seventh Report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure.

[9]Guidelines taken from the American Heart Association.

[10]Guidelines taken from the American Diabetes Association International Expert Committee as well as Cheng et al. (2009).

I show the descriptive statistics in Table 1 between individuals in HMOs and those in non-HMOs taken from data using all periods in the sample. I report the sample filtered down to the sample group and health insurance type. The variables are weighted by sample-year lives. The samples are approximately 14% black, slightly weighted toward female, approximately half have some college level education. The average age is about 57. Preventive care is measured with binary variables which equal one if the individual received the preventive measure and 0 if they did not. Respondents are asked if in the last two years, have they had any of the following medical tests or procedures: flu shot (Flu), cholesterol screening (Cholesterol), mammogram (Mammogram), Papanicolaou smear (Pap), prostate exams (Prostate), blood sugar testing (Diabetes), and blood pressure check (Blood pressure). I chose these measures because studies have found the benefits of these particular types of screening for this population outweigh the cost, at least through age 65.[11] Individuals do not answer all questions, men do not report mammograms or pap smears. Women do not report prostate exams, and they are not asked about mammograms if they have had a lumpectomy, or pap smears if they have undergone a hysterectomy. Individuals who report having diabetes or hypertension are assumed to have been tested for these diseases. These questions are asked every two years. That is the frequency or greater with which these tests were recommended for the applicable subgroup with the exception of prostate exams (usually greater than 2 years depending on other factors.) Table 1 shows that there is some association between preventive care and HMOs. In addition, individuals in HMOs have less net assets (average wealth) and lower wages than those in non-HMO plans. Participants of HMO plans are less likely to be married and more likely to be black. Despite this, health (or more precisely, predicted health, described below) remains similar among individuals in HMO and non-HMO plans.

Table 1 also has statistics for Hypertension miss, Diabetes miss, and High cholesterol miss. HMOs seem to have fewer individuals who are unaware of their underlying

[11]See Howard (2005); Walter et al. (2005); Tian et al. (2010); Maciosek et al. (2006) and the guidelines from the U.S.Preventive Services Task Force available at www.ahrq.gov/clinic/uspstfix.htm

conditions than non-HMOs. However, similar to the rate of preventive care screening tests, the difference is small and may not be statistically meaningful once other controls are included.

Overall, state of health is an important control variable in this analysis. Those in poor health may have frequent contact with providers who in turn may advise preventive care as part of diagnostic screening. However, using self-reported health has the potential of introducing a new vector for endogeneity to bias the effect of HMO status. This can happen if HMOs lead to more testing, which in turn unveils potential health problems, causing individuals in HMOs to report poor health. Then the effect of HMOs on preventive care would be diluted between self-reported health and insurance contract. To get around this issue, a health index is created using an auxiliary regression. This regression uses all control variables in the main regressions, as well as ten variables that measure Activities of Daily Living (ADL). ADLs are measures of functional health. Functional health is the ability to perform routine activities such as feeding oneself, bathing, dressing, grooming, working, homemaking, and leisure. Functional health is not influenced by knowledge about underlying health. Therefore, ADLs should not be directly affected by preventive screening. Consequently, the health index, created with the ADLs, will not be subject to the criticism that it biases the estimates of the variables of interest.[12] The health index is assumed to be a unidimensional latent variable. When asked for a self-report of health, individuals map latent health to an integer value between one and five (inclusive), which is then reported to the HRS. An estimate of latent health can then be created by using an ordered probit to regress self-reported health against the ADLs and other control variables. The coefficients become weights in a health index. These weights are then used to estimate latent health. The results of this procedure are reported in Appendix A.

[12]Bound et al. (1999) provides the framework and theoretical justification for constructing such a health index.

3 Results

In this section I test whether HMOs lead to greater use of preventive care services and better self-knowledge of one's health using several different specifications and outcome measures. I look at rates of preventive care by HMO status in Table 2. The first section labeled "Observational" shows the results for the entire sample without implementing the difference in differences approach. There I am able to replicate past results that show HMOs provide slightly more preventive care in columns 1-7, at least for cancer screens. The second and third sets of regressions look at the effect of HMOs for the non-HMO to HMO group and the HMO to non-HMO group respectively. In both cases, the results, for the most part, are small and insignificant at the 5% level. However, for cancer screenings the results are generally significant at the 10% level. This second and third set of results, and its difference from the first set of "Observational" regressions, is one of the main findings of this paper. Namely, that for cancer screenings, HMOs do seem to provide slightly more preventive care, although the confidence interval for these findings is wider than pure observational studies would find. Second, there does not seem to be a significant increase in flu shots or testing for diabetes, high blood pressure. The one difficult to determine measure is cholesterol testing, whose levels are higher for the HMO to non-HMO group but not the Non-HMO to HMO group.

It could be the case that HMOs perform more testing for individuals at different ages. Perhaps, for example, younger individuals will stay with the HMO longer and therefore testing will provide a greater net return to the HMO which HMO physicians somehow are able to internalize. To test this hypothesis, I examine the effect of HMOs on different age groups. I show the results in Table 3. Here again, although the observational results are in-line or slightly below past results, the effect seen for the difference in differences groups are smaller and insignificant. For the non-HMO to HMO group the only results that are significant are those for mammograms and pap smears at ages 50-54 where the effect sizes are 6 and 11 percentage points and prostate exams at ages 60-64 where the effect size is 7 percentage points. While statistically

significant on their own, there is a possibility that the hypothesis testing criteria is too weak given the large number of hypotheses being tested in the table.[13]

Table 4 examines missed diagnoses. Patients in HMOs and non-HMOs are equally likely to have a missed diagnosis. The differences are less than 1 percentage point and are both positive and negative for HMOs depending on the specification and sample group.

4 Conclusion

This study provides evidence of the causal impact of HMO membership on preventive care and several undiagnosed conditions. Seven common types of preventive care tests and three types of common chronic diseases whose diagnosis is strongly dependent on screening were analyzed. The evidence suggests that among middle-aged individuals, HMOs may have a small positive impact, but the effect is very mild and does not persist to older ages. Furthermore, the study is unique because it creates a better test of the use of preventive care by measuring its effectiveness. In other words, the study can answer the question: Are individuals with these underlying conditions actually being found through screening? For this purpose, I have presented rates of undiagnosed conditions. These rates are quite similar between HMO and non-HMO patients. Therefore, even if one believed HMOs caused increased usage of preventive care, it does not lead to better health knowledge than one might have received from a non-HMO type plan. The results are credible because a quasi-experiment, firm health plan turnover, deals with selection into and out of HMOs. The results differ between the estimator that uses a quasi-experiment and the one that does not. Of course, one possible source of this difference could be the difference in the experience of compliers to the quasi-experiment compared to non-compliers. If compliers are similar to non-compliers, then this suggests that selection is an important issue in determining the

[13]For comparison, Rizzo (2005) reports the effect of HMOs on pap smears as 9 percentage points, mammograms 7 percentage points, blood pressure, 6 percentage points, cholesterol tests 7 percentage points, and prostate exams 6 percentage points.

effect of managed care on the quality of care.

Table 1: Sample Statistics

	Non-HMO to HMO				HMO to non-HMO			
	HMO		Non-HMO		HMO		Non-HMO	
VARIABLES	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Mammogram	0.813	0.390	0.780	0.414	0.796	0.403	0.773	0.419
Pap	0.755	0.431	0.745	0.436	0.753	0.431	0.781	0.414
Prostate	0.681	0.467	0.641	0.480	0.675	0.468	0.686	0.465
Cholesterol	0.746	0.436	0.745	0.436	0.759	0.428	0.747	0.435
Flu	0.400	0.490	0.435	0.496	0.425	0.494	0.455	0.498
Blood Pressure	0.944	0.230	0.962	0.190	0.956	0.206	0.952	0.214
Diabetes	0.796	0.403	0.813	0.390	0.822	0.383	0.806	0.396
Hypertension miss	0.110	0.314	0.128	0.334	0.135	0.342	0.119	0.324
Diabetes miss	0.0488	0.216	0.0230	0.150	0.0332	0.180	0.0321	0.177
High cholesterol miss	0.0522	0.223	0.0407	0.198	0.0375	0.190	0.0333	0.180
Black	0.168	0.374	0.126	0.332	0.163	0.370	0.157	0.364
Female	0.561	0.496	0.547	0.498	0.548	0.498	0.568	0.495
College	0.0988	0.299	0.135	0.342	0.0943	0.292	0.108	0.311
Age	57.35	4.123	56.37	4.184	56.40	4.249	56.98	4.060
Avg household earn	$37,664	30,160	$40,795	32,876	$38,788	30,883	$38,470	28,549
Marriage	0.757	0.429	0.753	0.431	0.730	0.444	0.743	0.437
Wage	20.07	14.18	22.59	33.62	20.93	29.45	22.27	46.87
BMI	28.13	5.203	28.05	5.328	28.26	5.455	28.12	5.333
Predicted Health	1.352	0.397	1.384	0.401	1.339	0.393	1.372	0.405

Note: Data comes from the 1996-2010 waves of the HRS. Data further restricted to those between the ages of 45 and 65, with earnings between -$50,000 and $2,000,000. All monetary values deflated to 2010 values using the Consumer Price Index.

Table 2: Preventive Care and HMO Status

	(1) Mammogram	(2) Pap	(3) Prostate	(4) Cholesterol	(5) Flu	(6) Blood pressure	(7) Diabetes
Observational							
HMO	0.03***	0.01*	0.04***	0.02***	-0.00	0.00	0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Observations	16,434	16,415	12,062	28,476	28,545	12,656	19,140
R^2	0.04	0.03	0.06	0.04	0.06	0.02	0.02
Non-HMO to HMO							
HMO	0.03*	0.02	0.02	0.01	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	5,130	5,124	3,857	8,982	8,998	3,175	4,818
R^2	0.05	0.03	0.08	0.05	0.07	0.05	0.03
HMO to non-HMO							
HMO	0.04**	-0.02	0.04*	0.03*	-0.01	0.01	0.03
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Observations	3,396	3,391	2,580	5,964	5,979	2,284	3,573
R^2	0.05	0.05	0.07	0.05	0.06	0.06	0.03

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Regression of preventive care on HMO, age bins, marital status, race, gender, health, industry code, occupation code, household earnings, census division, health, and time fixed effects. Non-HMO to HMO refers to those with only one insurance option at work who were either in a non-HMO or who were switched by their employer from a non-HMO to an HMO. HMO to non-HMO is similarly defined.

Table 3: Preventive Care and HMO Status Interacted with Age

	(1) Mammogram	(2) Pap	(3) Prostate	(4) Cholesterol	(5) Flu	(6) Blood pressure	(7) Diabetes
Observational							
HMO X Age 45-49	0.04	-0.01	0.02	0.03	-0.00	-0.01	0.01
	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.02)	(0.03)
HMO X Age 50-54	0.04***	0.03**	0.03*	0.03***	-0.01	0.01	0.03**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
HMO X Age 55-59	0.01	-0.00	0.04***	0.02**	-0.01	0.01	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HMO X Age 60-64	0.03***	0.02*	0.03**	0.02*	0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	16,434	16,415	12,062	28,476	28,545	12,656	19,140
R^2	0.04	0.04	0.06	0.04	0.06	0.03	0.02
Non-HMO to HMO							
HMO X Age 45-49	0.08	0.03	0.08	0.04	0.02	-0.09*	-0.01
	(0.05)	(0.05)	(0.17)	(0.06)	(0.06)	(0.05)	(0.07)
HMO X Age 50-54	0.06**	0.11***	0.03	0.02	0.02	0.00	-0.01
	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
HMO X Age 55-59	-0.00	-0.01	-0.04	-0.00	-0.04*	-0.02	-0.03
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
HMO X Age 60-64	0.03	-0.01	0.07**	0.01	-0.00	0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	5,130	5,124	3,857	8,982	8,998	3,175	4,818
R^2	0.05	0.03	0.08	0.05	0.07	0.05	0.03
HMO to non-HMO							
HMO X Age 45-49	-0.02	-0.06	0.15	0.01	0.09	-0.04	0.16*
	(0.07)	(0.07)	(0.30)	(0.07)	(0.07)	(0.04)	(0.08)
HMO X Age 50-54	0.01	0.01	0.00	0.06**	-0.01	0.04	0.08**
	(0.04)	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)
HMO X Age 55-59	0.02	-0.04	0.03	0.02	-0.02	0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)
HMO X Age 60-64	0.08**	-0.00	0.07*	0.01	-0.01	0.01	0.02
	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02))
Observations	3,396	3,391	2,580	5,964	5,979	2,284	3,573
R^2	0.05	0.05	0.08	0.05	0.06	0.06	0.03

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Regression of preventive care on HMO, age bins, the interaction of the age bins and HMO status, marital status, race, gender, health, industry code, occupation code, household earnings, census division, health, and time fixed effects. Non-HMO to HMO refers to those with only one insurance option at work who were either in a non-HMO or who were switched by their employer from a non-HMO to an HMO. HMO to non-HMO is similarly defined.

Table 4: Effect of HMO Status on Undiagnosed Conditions

	(1)	(2)	(3)
VARIABLES	Hypertension miss	Diabetes miss	High cholesterol miss
Observational			
HMO	0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.01)
Observations	6,642	3,441	3,335
R^2	0.02	0.02	0.05
Non-HMO to HMO			
HMO	-0.00	0.01	0.01
	(0.03)	(0.02)	(0.02)
Observations	1,212	666	641
R^2	0.06	0.10	0.10
HMO to non-HMO			
HMO	-0.01	0.00	0.01
	(0.03)	(0.02)	(0.02)
Observations	1,660	921	889
R^2	0.04	0.07	0.09

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression of missed diagnosis on HMO, age bins, marital status, race, gender, health, industry code, occupation code, household earnings, census division, health, and time fixed effects. Non-HMO to HMO refers to those with only one insurance option at work who were either in a non-HMO or who were switched by their employer from a non-HMO to an HMO. HMO to non-HMO is similarly defined.

Table 5: Results of Ordered Probit of self-reported health on ADLs and Demographics

	Self Reported Health
Functional limitations	
Walk several blocks	-0.07***
	(0.00)
Walk one block	-0.05***
	(0.00)
Walk across room	-0.01
	(0.01)
Dress without help	-0.14***
	(0.01)
Bath without help	-0.11***
	(0.01)
Eat without help	-0.01
	(0.01)
Get in and out of bed	-0.21***
	(0.01)
Use toilet without help	-0.01
	(0.01)
Sit two hours	-0.05***
	(0.00)
Get up from chair	-0.27***
	(0.01)
Climb several flights of stairs	-0.01***
	(0.00)
Climb one flight of stairs	-0.03***
	(0.00)
Lift 10 pounds	-0.03***
	(0.00)
Kneel or stoop	-0.05***
	(0.00)
Reach above shoulders	-0.15***
	(0.00)
Push large objects	-0.02***
	(0.00)
Pick up dime	-0.06***
	(0.01)
N	140,165

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The results come from an ordered probit regression of self reported health against the ADLs and the demographic variables for race, sex, polynomial in age, wealth, education, industry and occupation dummies, and period dummies.

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A Appendix A

This appendix contains the results of the auxiliary regression of self-reported health on activities of daily living (ADLs) and the other exogenous variables from the preventive care equations. The predictions from this regression are used to generate predicted health. Predicted health does not directly contain information about the individual's knowledge of their cancer, diabetes, hypertension, or high cholesterol status. Therefore, predicted health does not suffer from the criticism that individuals who report being less healthy know they are less healthy because of knowledge gained from preventive tests which are caused by contract status. Constructing predicted health is done in the following manner.

1. Run an ordered probit of self reported health against the ADLs and other regressors in the model except contract status.
2. For each observation obtain a prediction of health using the coefficients on the ordered probit as linear weights.

This model stems from viewing reported health as coming from a latent health equation, where latent health, $health^{\star}$, is modeled as:

$$health^{\star}_{it} = \delta_{ADL} ADL_{it} + \delta_{\mathbf{X}} \mathbf{X_{it}} + \nu_{it}$$

The reported health equation then comes from the standard application of the ordered probit model to the latent equation. The variable, predicted health, is the estimated $\hat{health}^{\star}$ that comes from using the estimates of $\hat{\delta}_{ADL}$ and $\hat{\delta}_{\mathbf{X}}$ from running the ordered probit in step 1. Self-reported health is reported by the individual on a scale of one to five with five being the worst health state. The results reported in Table 5 show that being unable to perform ADLs is associated with worse health outcomes. With the exception of feeding oneself (eat) and

difficulty walking across a room (walkr), the coefficients for each variable are all significant at the 1% level. The pseudo R^2 is low, 0.09, but we expect low explanatory power as the model is trying to explain five different choices for the dependent variable.

B Appendix B

Cholesterol:[14] The sample studied in the HRS were assessed for TC and HDL. TC between 200 to 239 mg/dL is considered at risk and TC above 240 mg/dl is considered high. HDL is the "good" cholesterol, so higher numbers are considered better. HDL cholesterol less than 40 mg/dL for men, or less than 50 mg/dL for women, indicates a higher risk for heart disease. Ideally, these levels should be taken after fasting, that is not the case in the HRS. However, non-fasting levels of cholesterol are still useful as an evaluation tool.[15] In this study, TC above 200 mg/dL, HDL cholesterol less than 40 mg/dL (for men) or less than 50 mg/dL (for women) are considered high cholesterol in this study.[16] The HRS asks whether the individual received a cholesterol test in the past two years. Individuals who did not receive preventive cholesterol tests but did receive either TC or HDL levels that put them at risk for high cholesterol are considered to be missed opportunities for testing, labelled undiagnosed cholesterol in the tables

Hypertension: High blood pressure (hypertension) is determined by the amount of blood the heart pumps and the amount of resistance to blood flow in the arteries. Blood pressure is raised when the heart pumps harder and the arteries are narrower. Hypertension can go on for years without external symptoms. Uncontrolled hypertension is associated with serious health problems like heart attack and stroke. Hypertension can be assessed using systolic and diastolic blood pressure. Systolic blood pressure is the peak blood pressure in the arteries when the

[14]Blood cholesterol is a well-studied molecule in medicine. Cholesterol circulates bound to proteins and lipids, particles known as lipoproteins. The more studied molecules are High-Density-Lipoprotein Cholesterol (HDL), Low Density Lipoprotein Cholesterol (LDL-C) and Very-Low-Density-Lipoprotein Cholesterol (VLDL-C), and Total Cholesterol (TC).

[15]Non-fasting levels of cholesterol are believed to be more variable than fasting levels. Measurement error, in this case, will most likely attenuate any contract effects. This occurs because measurement error will make it appear as if those with high cholesterol have low cholesterol, and vice-versa. Therefore, the estimates shown are understatements of the true effect. Additionally, recent work by Sidhu and Naugler (2012) shows that the amount of variability added by taking nonfasting levels is negligible.

[16]Guidelines taken from the American Heart Association.

arteries are contracted. Diastolic pressure is the trough of blood pressure when the arteries are relaxed. Systolic and diastolic blood pressure are taken three times each in the interview, these numbers are averaged and compared against a cutoff value for hypertension. A range of values can be considered hypertensive, this study uses systolic pressure above 140 mmHg or diastolic pressure above 90 mmHg as the cutoff for hypertension.[17] The HRS asks individuals, "Has a doctor ever told you that you have high blood pressure or hypertension?" Individuals who have hypertension according to the cutoff but have not been told so by the doctor are considered a missed opportunity for testing, labelled undiagnosed hypertension in the tables..

Diabetes: Diabetes mellitus, or diabetes, is a group of metabolic diseases in which a person has high blood sugar because the pancreas does not produce insulin or the cells do not respond to insulin. Long-term, untreated diabetes can lead to cardiovascular disease and renal failure. The HRS takes several measures that could be used to construct a measure of diabetes risk. The measure chosen is Glycated hemoglobin (A1c). A1c measures the plasma glucose concentration over a period of time, usually about three months. Long-term high blood sugar increases the level of A1c. Following the recommendations of Cheng et al. (2009) levels above 6.5% are considered diabetic.[18] The HRS asks individuals, "Has a doctor ever told you that you have diabetes or high blood sugar?" Individuals who do not report a doctor informing them they have diabetes with A1c levels consistent with diabetes are considered a missed opportunity for testing, labelled undiagnosed diabetes in the tables.

[17]For more on these guidelines see the Seventh Report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure (JNC7)

[18]Currently, fasting blood glucose levels are also a component of diagnosing diabetes, but since they are unavailable in the HRS only the A1c is used. The American Diabetes Association International Expert Committee recommends a value of 6.5% as the cutoff to diagnose diabetes.