Pent-Up Demand and the Discovery of New Health Conditions after Medicare Enrollment

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Abstract: Recent evidence shows that those who obtain insurance coverage via Medicare at age 65 experience increases in the utilization of certain types of preventive and curative care that are larger than those experiences by the previously insured. Insurance coverage may lead to a "discovery effect" where new conditions are diagnosed once better access to medical care is available. Here, Cox relative risk models are used on a sample of respondents from the Health and Retirement Study to assess the differential rate of new diagnoses of chronic conditions upon enrolling on Medicare. My results here indicate a higher rate of increase in the diagnosis of most chronic conditions among the previously uninsured relative to the insured upon obtaining Medicare coverage. Because failing to obtain a timely diagnosis can lead to improper disease management and poorer health outcomes, these results suggest that access to care for the uninsured prior to age 65 may improve health trajectories of Medicare recipients. The additional increase in diagnosis after Medicare among the previously uninsured also implies that using chronic conditions as an assessment of the relative health of the uninsured is inadequate.

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The relationship between health insurance and health is an important policy issue, as evidenced by the recent Institute of Medicine series on the consequences of uninsurance. One book in that series, *Care without Coverage: Too Little, Too Late* (2002), finds that the uninsured receive too little medical care, receive care in an untimely fashion, and consequently have worse health outcomes and increased mortality risk. In a summary of the literature, Hadley (2003) finds that the uninsured receive less diagnostic, curative, and preventive care and are in worse health at the time of diagnosis. If health is measured by the presence of chronic conditions, then cross-sectional studies that study the relationship between health insurance and health may be flawed. If the uninsured are unable to obtain access to care and timely diagnosis, then the uninsured may appear relatively healthy compared to their insured counterparts who are able to receive proper diagnosis. This study is able to provide some evidence of the inadequacy of the use of chronic conditions as a measure of the health status of the uninsured by focusing on the rate of change in diagnosis that occurs after Medicare enrollment at age 65. The lack of access to care while uninsured implies that if health insurance coverage becomes available, individuals may increase their medical care utilization in order to treat known illnesses or receive diagnosis for symptoms.

Medicare is an excellent source of health insurance variation because virtually everyone in the United States with adequate work history becomes eligible for coverage at age 65, regardless of health status. This health insurance transition therefore avoids some of the health selection issues normally associated with insurance coverage at younger ages. Though there is mixed evidence on the effect of insurance transitions on utilization changes at younger ages,[1] recent evidence using hospital discharge data has shown increases in many forms of medical care utilization after age 65 (Lichtenberg, 2002, Card, Dobkin, and Maestas, 2004).[2] Other studies have used longitudinal survey data to study the changes by prior insurance status in utilization and expenditures that individuals experience as they reach Medicare eligibility. McWilliams et

[1] Long, Marquis, and Rodgers (1998), Card, Dobkin, and Maestas (2004), and the RAND Health Insurance Experiment (Manning et al., 1987 and Newhouse, 1993) found little evidence of health insurance transitions leading to changes in utilization behavior. Taylor (2003) notes that the evidence regarding insurance transitions onto public programs and utilization changes is somewhat mixed, and recent evidence by Tchernis et al. (2005) suggests that individuals do alter utilization in response to insurance changes.

[2] Finkelstein (2005) shows that the introduction of Medicare in 1965 brought about large changes in the introduction of new medical technologies and the way medicine was practiced, and also led to large aggregate changes in total medical expenditures. Finkelstein and McKnight (2005) also find that it significantly reduced individual out-of-pocket costs.

al. (2003) finds that the acquisition of Medicare coverage narrowed the gap in preventive care utilization between the previously uninsured and insured.[3] Schimmel (2005) shows that the previously uninsured experience larger increases in the use of physician services, outpatient surgery, home health care, and total medical spending than those who were continuously insured. A large portion of this increased utilization is attributed to pent-up demand prior to age 65, that is, the storing-up of medical care in anticipation of future insurance coverage. Recent work has also studied Medicare's effects on health outcomes and has found modest gains in self-rated health (Card, Dobkin, and Maestas, 2004) as well as an increase in the probability of being diagnosed with breast cancer among white women after Medicare enrollment (Decker and Rappaport, 2002).

Increases in utilization upon obtaining insurance coverage may occur because the uninsured have known health conditions that have not received proper treatment, leading to a catch-up effect to restore health once enrolled on Medicare. The increased utilization may also arise because individuals seek treatment for already diagnosed conditions, for symptoms without a diagnosis, or because diagnostic tests encounter asymptomatic conditions requiring additional treatment. The "discovery effect," a term coined by Donabedian (1976), refers to the knowledge one gains about individual health status upon obtaining access to medical care. This effect predicts that the increase in diagnosis will be larger for those who obtain insurance coverage once enrolling on Medicare, as these individuals are likely to experience larger increases in health care utilization and contacts with the medical system than those who have continuous insurance coverage. This in turn leads to a higher probability of receiving a new diagnosis of a particular condition. The discovery effect will be more important for conditions which are chronic in nature rather than acute conditions which require immediate attention. For example, a man who is uninsured having extreme chest pain will not wait to seek medical attention until he is insured, but instead will seek treatment quickly for symptoms of a heart attack.[4] This effect is also expected to be larger among conditions that are harder to self-diagnose or asymptomatic, as

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[3] Sudano and Baker (2003) documented a lower use preventive care use among the uninsured near-elderly and that even after obtaining insurance, some period of time is needed to reestablish clinically appropriate care regimens.

[4] However, it is possible to have a "silent" heart attack or stroke and not learn about it until later diagnostic tests reveal past incidents. Thus, it may be possible for the previously uninsured to experience higher rates of diagnosis upon receiving medical care due to Medicare coverage, even if the more acute types of medical conditions occurred in the past.

an individual will likely not know the underlying cause of the problem until seeking medical attention.

Longitudinal data from the Health and Retirement Study (HRS) is used here to follow a panel of individuals from 1992 onward as they progress from ages 56-61 to Medicare enrollment at age 65 and then for several years after age 65. The HRS contains a wide battery of demographic and socioeconomic variables that influence health, as well as information on current health insurance status and a variety of measures of health status across time. At each interview, HRS respondents are asked whether a doctor has ever told them that they have: a heart condition, a lung condition, high blood pressure, diabetes, cancer, stroke, or arthritis. By comparing responses across interviews, it is possible to isolate the timing of a new diagnosis. Because the discovery effect occurs as a result of increased medical care utilization, it is expected that the incidence of new diagnoses will be higher in the years immediately following Medicare enrollment. In order to test the discovery effect hypothesis, Cox relative risk models with time-varying covariates are used to assess the differential rate of failure (diagnosis) after age 65 by insurance status prior to Medicare.

Results in this paper indicate that the increased utilization experienced after age 65 by those who were uninsured prior to Medicare leads to an elevated hazard of diagnosis relative to the insured for virtually every chronic condition considered for both men and women. The magnitudes of these effects are clinically meaningful; differential increases after Medicare are between 20% and 400% larger among the previously uninsured compared to the insured. These effects are particularly strong for men with heart conditions and for women with lung conditions or cancer. Smaller effects are found for other conditions such as diabetes and high blood pressure, but there is still an elevated risk of diagnosis among the previously uninsured. The timing of increased diagnosis corresponds to the increases in utilization found in Schimmel (2005), indicating that most of the effect operates within the first few years of Medicare coverage as a result of pent-up demand. Estimates from the Cox models also show that the previously uninsured are less likely to be diagnosed compared to those who were insured in the years prior to Medicare.

Though many of the results do not achieve statistical significance, the point estimates are robust to specification changes and consistent across health conditions, suggesting that additional data will lead to more precisely estimated effects of the same magnitude. The combination of additional increases in medical care utilization and in the diagnosis of chronic conditions among the uninsured after age 65 is compelling evidence that the uninsured are in fact sicker prior to obtaining Medicare coverage. These findings suggest that those who are uninsured prior to Medicare are in worse health overall, but have conditions that remain undiagnosed until access to care can be obtained. Thus, judging the health of the uninsured by considering only the presence of chronic conditions may be a poor way to assess the true health status because the lack of diagnosis would mean the uninsured are sicker than they appear. Comparisons of the uninsured to the insured based on chronic conditions would make the health disparities between the two groups appear smaller than it actually is. If the uninsured delay their health care until their condition is more serious, it may lead to a lower health stock and more expensive treatment to restore health once covered. This implies that an extension of Medicare or another health insurance option to provide continuous care in the pre-Medicare years could have significant effects on the health trajectories of otherwise uninsured individuals as they age.

This paper proceeds as follows. Section 1 presents the Cox relative risk framework with time-varying covariates and discusses some confounding factors which affect the time path of observed diagnosis. Section 2 discusses the advantages of the Health and Retirement Study to address this question and provides a description of the sample used here as well as some basic descriptive statistics about health status and the prevalence of health conditions in this age group. Section 3 presents the estimation results and robustness checks. Section 4 concludes with a discussion of the important intertemporal effects of health insurance on health and directions for future work.

1. Survival Analysis Framework for Estimating the Discovery Effect

1.1. Cox Relative Risk Models with Time-Varying Covariates

The nature of questions about chronic conditions in the HRS is such that once an individual is diagnosed with a particular condition, the respondent will always have such a diagnosis. Hazard models are ideal for this type of absorbing state data and can be used to assess the time until failure, which here corresponds to the wave of first diagnosis. Cox relative risk models with time varying covariates (Lancaster, 1990, Kalbfleisch and Prentice, 2002) are quite flexible because coefficients can be estimated without calculating the baseline hazard $\lambda_0(t)$ (Neumann, 1999). The hazard function is defined as:

$$\lambda[t;X(t)] = P\{T \in [t,t+dt) \mid X(t), T \geq t\}/dt$$
$$= \lambda_o(t) r[t;X(t)] \tag{2.1}$$

r[t;X(t)] is the function relating the covariates to the hazard and is specified in the Cox model as r[t;X(t)]=exp[X(t)'β]. The likelihood function of this model is given by:

$$L(\beta) = \prod_{j=1}^{k} \frac{\exp[X_j(t_j)'\beta]}{\sum_{\ell \in R(t_j)} \exp[X_\ell(t_j)'\beta]} \tag{2.2}$$

$R(t_j)$ denotes the risk set at time t_j; observations that have already failed or are right-censored are excluded for the likelihood function at that time. Upon being first diagnosed with a condition, the individual will subsequently be excluded from the risk set for that particular condition. Thus, the risk set will be smaller for conditions that already have a high level of diagnosis at the baseline interview at ages 56-61 (for example, arthritis and high blood pressure) compared to conditions with low prevalence (cancer, for example).

The model specification used to separate the previous diagnosis effect and discovery effect for each chronic condition is similar to that used in Schimmel (2005):

$$\exp[X(t)'\beta] = \exp[X'_i\,\beta_1 + X'_{it}\,\beta_2 + \beta_3 \cdot medicare_{it} + \beta_4 \cdot unins_i + \beta_5 \cdot intins_i + \beta_6 \cdot (unins_i \cdot medicare_{it}) + \beta_7 \cdot (intins_i \cdot medicare_{it}) + \varepsilon_{it}] \tag{2.3}$$

The Cox relative risk models have no intercept because it is subsumed in the baseline hazard which is not estimated.[5] Control variables include X_i and X_{it}, which consist of time-constant and time-varying variables, respectively. Exponentiated coefficients report the hazard ratio relative to the reference group, which consists those who were continuously insured in the waves prior to Medicare enrollment.[6]

The variable *medicare*$_{it}$ is a dummy variable for whether individual i is covered by Medicare and is age 65 or older in period t. This variable changes over time, but once on Medicare, the individual stays on Medicare for the duration of the panel. Since a quadratic in age is contained in X_{it}, this coefficient captures the independent effect of Medicare on diagnosis, beyond the effects of age. β_3 represents the change in the rate of diagnosis for the continuously

[5] In order to account for unobserved individual heterogeneity, another alternative would be conditional fixed effects logit models. However, these models are less efficient for studying this problem because they do not exploit the time variation in diagnosis. Unobserved individual heterogeneity is subsumed in the nonparametric baseline hazard of the Cox model, and thus no additional individual fixed effect is needed.

[6] For example, Cleves, Gould and Gutierrez (2002) provide an example that if the coefficient on age is 0.18, then a one-year increase in age leads to an exp(0.18)=1.20, or 20%, increase in the hazard. Results reported below will already be converted to hazard ratios for ease of interpretation,

insured group after Medicare enrollment relative to their hazard rate of 1 prior to Medicare enrollment. Even among the previously insured, enrollment onto Medicare may require a switch to a new provider or lead to a check-up which may lead to the diagnosis of new health conditions. Thus, $\exp(\beta_3)$ is expected to be close to or greater than one.

The coefficients on the dichotomous variables of continuous uninsurance ($unins_i$) and intermittent insurance ($intins_i$) denote the hazard ratio of being diagnosed with a particular chronic condition for each insurance type relative to the continuously insured group prior to Medicare. The magnitude of these coefficients is not clear due to the offsetting effects of the diagnosis and health selection effects.[7] If the uninsured are less healthy and therefore are more likely to receive a diagnosis prior to age 65, then $\exp(\beta_4)>\exp(\beta_5)>1$. However, if the uninsured lack access to care that would lead to diagnosis, then it would be expected that $\exp(\beta_4)< \exp(\beta_5)<1$. These effects may offset each other and are discussed in more detail below. The coefficients on the interaction terms between Medicare and previous insurance status indicate the differential hazard ratio of diagnosis upon enrolling in Medicare of the continuously uninsured (β_6) and intermittently insured (β_7) relative to the continuously insured prior to Medicare. The discovery effect predicts that groups without continuous coverage will have a higher hazard of new diagnosis at age 65 than those who had continuous coverage, so that $\exp(\beta_6)$ and $\exp(\beta_7)$ are expected to be greater than one. Because those who are continuously uninsured are likely to have had less access to medical care than the intermittently insured, the discovery effect also predicts that $\exp(\beta_6)>\exp(\beta_7)>1$ for the chronic conditions considered here.

1.2. Confounders to Estimating the Discovery Effect

Studying the discovery effect is made difficult by the fact that one's insurance path throughout their life will have affected their health trajectory and the diagnosis of new conditions, thus affecting whether or not they are currently at risk for a new diagnosis. If an individual is persistently in poor health, he will be more likely to have already obtained a diagnosis of a chronic condition in the past. If this person has already obtained a diagnosis by a particular time, he is not at risk of a new diagnosis of that same condition and thus would be excluded from the risk set. However, on the other hand, if an uninsured individual is chronically ill but lacks access to medical care, he is less likely to have already obtained a proper diagnosis.

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[7] The health selection here assumes that the uninsured are less healthy, which as discussed later, seems to be a reasonable assumption based on observables in the sample.

Thus, when studying the discovery effect at a particular point in time, especially late in the life course, the individual's insurance trajectory over the lifetime will determine whether a new diagnosis is possible. At middle age, the risk set of those who have yet to fail may contain more previously insured individuals than those who lacked insurance coverage.

Though researchers are generally interested in estimating the causal influence of health insurance on health outcomes, the *health selection effect* posits that the uninsured are actually less healthy to begin with, and this lower health stock influences the ability to obtain or maintain health insurance. Those in worse health could become uninsured if poor health prevents them from working and therefore decreases the likelihood of obtaining employer-sponsored health insurance. The less healthy could also be less likely to be uninsured if pre-existing conditions or high insurance premiums makes it difficult to obtain coverage. This selection effect leads to difficulties in interpreting causality because it is not clear when observing individuals at a point in time whether the worse health status of the uninsured is caused by the lack of insurance or if their health status was worse to begin with. This endogeneity is the reason that Levy and Meltzer (2004) conclude that cross-sectional observational studies studying the effect of health insurance on health are often flawed. Recent examples using the HRS found that the uninsured have worse health trajectories as they age (Baker et al., 2001) and that they have higher mortality risk (McWilliams et at., 2004), but neither of these studies addressed the endogeneity of health insurance and health.

Though the health selection effect generally predicts that those without health insurance are in worse health, there is also the possibility that the relationship runs in the other direction. This reverse selection would be the case if healthier individuals believed that they did not need to purchase health insurance, and instead chose to self-insure using their own wealth. Throughout most of the life course, this is unlikely to be the case, but may be more common as individuals approach Medicare. Because individuals can retire under current Social Security rules at age 62 but are not eligible for Medicare until age 65, there may be some portion of the population who decides to self-insure for the time between retirement and Medicare enrollment. Some individuals may also choose to partially retire at younger ages by choosing self-employment, therefore foregoing insurance coverage offered from their previous employer. While reverse selection may be likely in older populations than at younger ages, the demographic, economic and health characteristics of the sample here indicate that health selection runs in the expected direction on average. Those who are uninsured are generally of lower socioeconomic status, more likely to be a minority, and have worse self-reported health and difficulties with daily tasks. Thus, the remainder of the paper will assume health selection implies those in worse health are more likely to be the uninsured.

Though the uninsured may be in worse health, the lack of access to medical care may lead to a lower level of diagnosis among the uninsured than the insured.[8] If the true level of illness among the uninsured is higher than that of the insured, but the former do not obtain a diagnosis, it may appear in a cross-section that the level of illness is about the same between the two groups, or possibly even lower among the uninsured. The *diagnosis effect* occurs because past insurance status affects whether one has already been diagnosed with a condition. Those who have had insurance and more access to care will be more likely to already have a diagnosis than an individual who has lacked coverage. Because the health selection effect and the diagnosis effect may have offset each other, cross-section data that focuses on the rate of a particular condition as evidence of the relative health status of the uninsured may be flawed. The use of longitudinal data, which can study the change in diagnosis and the discovery effect upon obtaining health insurance, is a more suitable way to gauge the relative health of the uninsured.

2. Description of Health Insurance and Health Conditions Data in the HRS

2.1. Data Description and Sample Selection

The Health and Retirement Study is a nationally representative sample of the non-institutionalized population in the United States over the age of 50. In 1992, an original cohort of respondents born between 1931 and 1941 and their spouses were interviewed, and those individuals have subsequently been interviewed every other calendar year since. A wide range of information is collected about respondents including work and retirement behavior, health insurance coverage, and health status measured in a variety of ways. The panel used here consists of a sample of the original 1992 age-eligible HRS cohort, using data from core interviews in waves 1992-2002 (6 waves).[9] All individuals in the sample were initially

[8] The identification strategy here relies on the rates of new diagnosis as opposed to the levels. The underlying hypothesis is that the rate of new diagnosis is the same between both groups prior to Medicare enrollment, even if the base levels of diagnosis differ between the two groups. Upon reaching Medicare enrollment, the discovery effect predicts an increase in the rate of diagnosis among the uninsured. This identifying assumption is tested in the empirical section.

[9] HRS respondents who are unable to complete their own interview are able to have a proxy do the interview for them. Only core interviews done by the individual are considered here, proxies are excluded.

interviewed in 1992, have been observed to turn age 65 and subsequently accepted Medicare coverage during the study, and have available information on insurance coverage in the two waves immediately prior to their first interview covered by Medicare. Those who had Medicare coverage prior to age 65 are excluded from the sample altogether because in their case Medicare coverage is offered in response to a terminal health condition and therefore there is a correlation between health and insurance status. Individuals from the original cohort who have been observed to turn 65 were born in 1931-1937 and had their 65th birthdays observed in the 1996, 1998, 2000, or 2002 HRS interviews.[10]

Based on these criteria, the sample to be considered here consists of 3,392 individuals who meet the selection criteria named above. 314 first received Medicare and were over 65 in 1996, 944 in 1998, 992 in 2000, and 1,142 in 2002. There were 12 individuals who died between 1996 and 1998, 42 between 1998 and 2000, and 88 between 2000 and 2002, a relatively small group compared to the overall sample.[11] These individuals are included until their death but are right-censored beginning in the wave their death was reported. Individuals are not required to have been interviewed in every HRS interview wave and in cases of missed interviews, the time period for new diagnosis is adjusted accordingly. For example, someone who was interviewed in 1992, not in 1994, but again in 1996, and reports the new diagnosis in 1996, the time period for the diagnosis is four years instead of two. Overall, there are 19,737 person-wave observations to be considered for study (the actual number available for analysis varies by each condition due to differing time to failures and censoring).

The nature of the HRS panel raises some common difficulties that arise when using duration analysis. First, because the sample considered that was initially interviewed in 1992 at ages 56-61, some proportion of the sample has already been diagnosed with the condition upon entry. These individuals must be excluded from the risk set because they have already failed at an unspecified time prior to entry. Left truncation is fairly standard, but is difficult because the likelihood of diagnosis at entry is correlated with prior insurance status. Assuming that the

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[10] Because these individuals were of different ages at their baseline interview, the older groups could be more likely to have been already diagnosed with chronic health conditions, though the difference between these ages is actually minimal. Age controls in these models should capture any remaining effects of age.

[11] Reports from after-death proxy interviews indicate that there are actually relatively few new diagnoses of new conditions in the period before death. For example, among the 42 who died between the 1998 and 2000 interview, there was only one new diagnosis of a lung condition, 2 new stroke diagnoses, and 6 new cancer diagnoses. These new diagnoses are small relative to the number of deaths and the number of new incidence in the 2000 wave. In order to avoid potential issues with the accuracy of proxy reports, the data from the proxy interview is excluded.

underlying health status of the two groups is the same, the fact that the insured are more likely to have a diagnosis of a chronic condition at baseline means that they will have a smaller risk set at entry. However, because the diagnosis of new conditions upon receiving Medicare coverage is precisely the point of estimating the discovery effect, the left truncation of the data should not pose serious problems. Next, because the survey is ongoing, many of the observations are right-censored at the last interview year or upon earlier exit from the study due to attrition or death. Many individuals have not been diagnosed with a condition by their last HRS interview. Nonetheless, the Cox model easily deals with this type of censoring, as long as it is assumed to be independent from the failure process.[12] Finally, the last issue relates to the time period between HRS interview waves and the way ties are handled in calculating the likelihood function. Because all of the observations that report failure at a particular interview wave did not fail simultaneously, a method for determining the order of failure within the two years between HRS interviews must be used. The desired calculation to model the HRS data is the exact marginal calculation, which relies on the use of continuous time to assume that no two failures occurred at the same time (Cleves, Gould, and Gutierrez, 2002). The standard Breslow approximation is used in place of the exact marginal calculation in order to include Huber-White heteroskedasticity robust standard errors.[13]

Control variables included in the model are time-constant and time-varying covariates that are thought to influence health. Because men and women are affected differently by various health conditions, many results are reported separately by gender. The construction of other covariates corresponds to the way they were reported in Table 1 (except for age which is specified using months and includes a quadratic term, and veteran status which is included in models for male only). Time-constant variables include demographics such as categorical variables for education level and indicators for black and Hispanic. The remaining variables are time-varying covariates which include current marital status, census region of residence, and

[12] This may not in fact be completely accurate since many of those who attrite from the survey and those who die are in worse health than those who continue to be interviewed. The number of individuals who missed interviews for reasons other than death is also quite small: 82 in 1994, 62 in 1996, 44 in 1998, 56 in 2000, and as many as 146 in 2002 (the RAND HRS data used here did not include the final release of the 2002 HRS, so some reasons for missed interviews were not yet known). The vast majority of individuals who missed one interview were subsequently interviewed in the next wave.

[13] Stata does not estimate Cox models with both the exact marginal calculation and robust standard errors, so the latter was chosen as an option. However, the results are not qualitatively different if the exact marginal calculation with non-robust standard errors are chosen.

economic measures such as currently working for pay, current self-reported retirement status, annual household income and total household wealth. Time-varying covariates such as smoking status (current and ever), current drinking behavior, body mass index, and summary measures for functional limitations, CESD score for depressive symptoms, and ADL (activities of daily living) and IADL (instrumental activities of daily living) difficulties are included in some models.[14] All time-varying measures are measured using the previous wave report, to avoid issues of timing between interview waves. For example, someone who has had a heart attack since the previous wave may have lower income now due to the inability to work, but that would not have causally affected the health condition.

Self-reported health is excluded as a variable predicting the diagnosis of conditions because of concerns that this variable is more subjective in nature than other measures of health status. Measures of health behaviors and other more objective measures of health discussed above should capture changes in health status, and the inclusion of self-rated health in the models did not affect the coefficients of interest in a meaningful way. Though the discovery effect is thought to affect the diagnosis of conditions through the increase in access and medical care utilization brought about by insurance coverage, separate measures of utilization are not included in this model for two reasons. The first is that by excluding such variables, the Medicare variable captures the increased utilization it brings about in a single summary measure. The second reason is that the HRS data cannot distinguish when the utilization occurred in relation to the diagnosis of a condition. It is not clear in the data whether any changes in utilization lead to a diagnosis or whether the diagnosis leads to the utilization increase. Any changes in medical care use that occur after the age of 65 will be captured by the Medicare variable, meaning that variable will be a proxy for utilization.

2.2. Insurance Coverage in the Population Approaching Medicare Eligibility

Though Medicare coverage can vary on a number of dimensions, a single dichotomous variable for whether an individual is currently covered by Medicare and is over the age of 65 is used. The first wave in which this variable equals one will be referred to as the "first Medicare wave." 93% of HRS respondents have Part B coverage along with Part A, meaning that for most, this binary definition suffices. There is no statistically significant difference by insurance status prior to Medicare in the percent of the population with Part B or Medicare HMO coverage

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[14] These summary measures are described in more detail in Appendix 1.

once enrolled. While supplemental health insurance and Medigap policies may also affect utilization after enrollment, this variation is less exogenous than the switch onto Medicare since an individual has to decide whether to seek out that alternative coverage. To avoid the endogeneity issues associated with that choice, supplemental coverage will not be included as a separate insurance variable. Instead, Medicare will be a single dichotomous variable denoting having any type of Medicare coverage, which may or may not also include supplemental coverage.

Questions to ascertain an individual's current source of insurance coverage are asked in each wave of the HRS. Respondents are asked about public coverage via Medicare, Medicaid, and Champus/VA coverage (though those who received Medicare prior to age 65 are excluded from the sample here). Individuals are asked whether their private insurance coverage is obtained from their current or former employer, their spouse's current or former employer, or another source. An individual is categorized as insured in a single wave if they report coverage from any of the aforementioned sources. Because the HRS only asks point-in-time questions about insurance status, someone who did not have insurance for the majority of a two-year period but obtained coverage immediately prior to their HRS interview would be coded as having insurance coverage for the previous two years.[15] To account for longer uninsurance spells, insurance status as used here is defined using the two interview waves immediately prior to the first wave an individual is over 65 and covered by Medicare. This definition follows that used in Baker et al. (2001), Sudano and Baker (2003), McWilliams et al. (2003), and Schimmel (2005). Using these two waves, three categories of insurance status are created: continuously insured (insurance in both period), continuously uninsured (uninsured in both periods) and intermittently insured (insured for one period and uninsured for one period). These insurance variables are constant within individual over time, so that individuals are "typed" by the insurance coverage they had prior to Medicare.[16]

Among the sample of 3,392, 80.13% were continuously insured for both periods prior to Medicare enrollment. 7.42% were continuously uninsured before Medicare and an additional

[15] In later waves of the HRS, individuals are asked if they have been uninsured at all since their last interview. To define insurance status consistently across time, this variable was not used because it is not available in all years.

[16] This insurance definition means that the health insurance time period considered here may be shorter than the time period in which health events are observed to occur. For example, someone who turned 65 in 2002 will have been under study and able to suffer a new diagnosis beginning in the 1994 wave, but their insurance status will only have been defined using 1996 and 1998 insurance data. Thus, the health failure may predate the insurance categorization, but in order to be consistent across available data, a two-period measure was chosen.

12.45% of respondents were intermittently insured, meaning that they were uninsured for one of the two periods.[17] This intermittent group is almost evenly divided between those who were uninsured then insured (47%) and those who were insured versus uninsured (53%). The pattern of intermittent coverage may be expected to affect patterns of utilization once insured, but these groups are pooled as one. The intermittently insured are expected to be less susceptible to the discovery effect than those who were continuously uninsured, so subsequent discussions will primarily focus on the continuously uninsured.

Table 1 presents descriptive statistics by insurance group at the baseline interview in 1992, separately for men and women. All insurance groups had a mean age at the baseline interview in 1992 of 58 years, meaning that differences in health status at baseline should not be driven by age differences. The differences in demographic and economic variables between these groups confirm the usual finding that the uninsured are more likely to be less educated, minority, and have a lower socioeconomic status. The continuously uninsured and intermittently insured groups have lower means levels of education than the continuously insured and are also more likely to be black or Hispanic. Men and women who are continuously insured are considerably more likely to be married than other insurance groups. There are also differences by insurance category in work behavior: the uninsured are less likely to be working for pay but also less likely to consider themselves retired, perhaps reflecting health conditions that are limiting the ability to work. These differences in work behavior may also be driving the large disparity in income and wealth between the continuously uninsured and insured groups: the insured have annual income that is twice as high and have household wealth that is about double that of the uninsured group.

The differences in health status and health behaviors by insurance group indicate that the uninsured have worse health behaviors and may be in poorer overall health. The continuously uninsured have much higher rates of smoking (both ever and current) than the continuously insured, suggesting that this group will have adverse health consequences as a result. The

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[17] Baker and Sudano (2005) find that uninsurance is 2-3 times higher using all waves of HRS data from 1992-2002 than a single cross-sectional estimate. In the sample here, there is also evidence that there is transition out of the continuous insurance states if three periods are used instead of two: (21-38% of the continuously uninsured would become intermittently covered if three waves were used, 5-8% of the continuously insured would be categorized as intermittently insured with three waves). Given this transition out of the continuous states into the intermittent group, the differential change between the continuously uninsured and continuously insured will be biased towards zero compared to results using more waves of insurance status.

uninsured are less likely to drink, but this variable only detects any drinking not the quantity of drinking. In fact, certain forms of alcohol such as wine may have protective effects against some health conditions, so it may not be unexpected that the insured have a higher amount of any drinking. Mean body mass index is not different between the groups, but fewer of the uninsured are in the healthy BMI range compared to the insured. Evidence of the possible importance of the diagnosis effect comes in the difference between self-reported health difficulties and the number of chronic conditions. Though the uninsured report themselves in worse overall health, have more functional limitations, more depressive symptoms, and more difficulties with activities of daily living (ADLs) and instrumental activities of daily living (IADLs), there is little difference in the number of diagnosed conditions between groups. These health difficulties indicate that health selection likely runs in the traditional direction, that is, the uninsured are less health than their insured counterparts. The small difference in the number chronic health conditions among the uninsured, despite what appears to be overall worse health on other dimensions, suggests that the diagnosis effect dominates the health selection effect.

2.3. Baseline Health Status and the Diagnosis of New Health Conditions

Each interview wave, HRS respondents are asked a series of questions about their current health status. Included in this series are questions about the diagnosis of a number of types of chronic illness.[18] At the baseline interview in 1992, individuals were asked if a doctor has ever told them that they have: a heart condition (myocardial infarction, congestive heart failure, coronary heart disease, angina, or other conditions), chronic lung disease (chronic bronchitis, emphysema, but excluding asthma), high blood pressure/hypertension, diabetes/high blood sugar, a stroke, or cancer (malignant, non-skin cancer).[19] HRS respondents also report whether they believe they have or whether a doctor has ever told them they have arthritis (or rheumatism). Because individuals are able to self-diagnose themselves with arthritis, there may be less evidence of the diagnosis effect and discovery effect than for other conditions requiring a doctor's diagnosis. In interviews after baseline, individuals who have not already reported a condition in a previous interview are asked about new diagnoses since the previous interview.[20]

[18] See Fisher et al. (2005) for a documentation of the health measures collected by the HRS.

[19] Because a small number of new strokes are reported overall, this condition will be excluded from the analysis until additional cases can be obtained in future waves of data.

[20] In later waves, individuals are allowed to dispute the information they gave in a previous interview. For example, someone who said they had a new heart condition in 1996 can dispute that record in their 1998 interview. For some conditions, the way in which these disputes are handled can lead to different sample means of ever diagnosed.

Thus, a consistent measure of the rate of "ever diagnosed" can be constructed across waves. However, note that these questions do not require the current presence of a condition. For example, someone who was told by their doctor four years ago that they had high blood pressure may have since changed diet and exercise habits and no longer have high blood pressure. Because of this, the HRS "ever diagnosed" questions do not indicate disease prevalence. Nonetheless, they are useful for studying the diagnosis effect because being told by a doctor requires utilization of medical care. The new diagnoses that occur between waves can be roughly thought of as the two-year incidence rate.

Table 2 presents the percent of males and females in the sample who have been diagnosed with each of the conditions at the baseline interview in 1992 (prior to Medicare) and by the 2002 HRS interview (after Medicare enrollment). At baseline, continuously insured men have higher diagnosis levels of arthritis and heart conditions than the uninsured, suggesting that insurance status has contributed to increased diagnosis. The continuously uninsured men have higher diagnosis levels of lung disease and diabetes compared to the insured, perhaps as a result of poor health behaviors such as smoking and obesity. By 2002, insured men have higher diagnosis levels of heart conditions and high blood pressure but have slightly lower levels of diagnosis of diabetes, arthritis, and cancer. The increase in diagnosis levels among the uninsured between 1992 and 2002 suggests that new insurance coverage may lead to the discovery of chronic conditions. The story for women is somewhat different. In both 1992 and 2002, continuously uninsured women have higher levels of lung conditions, high blood pressure, diabetes and stroke their continuously insured counterparts. Other levels are about the same between the two insurance groups.

The identification strategy used here that compares the differential rate of new diagnosis by prior insurance status rests on the assumption that the true underlying onset rate of illness in the population is the same among the uninsured and the insured. One simple way to test this assumption is to study trends in the rate of new diagnoses prior to age 65. A simple descriptive way to do this is to consider the cohorts who first enrolled on Medicare in 1998, 2000, and 2002,

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Using information on these disputes, a cross-wave consistent measure was constructed. If an individual ever reports a condition and does not dispute it, the value for that variable will be one in all interviews subsequently. However, if someone reported a condition and later disputed it, all earlier waves in which a person reported the condition will be set to zero. This creates an absorbing state value of "ever diagnosed." However, these disputed cases are rare, ranging from around 1% of responses in each wave for variables such as heart and lung conditions, up to 3% of responses for arthritis. Because the frequency of these disputes is low, the way in which these disputes are handled should not affect results here.

in order to have three waves of data prior to Medicare. One can then compare the percentage change in "ever diagnosed" between three periods before and one period before Medicare enrollment by prior insurance status. Though the percentage change in diagnosis across this time period is slightly higher among the previously insured, the rates of change are similar enough in most cases that the assumption that the two groups have the same rate of disease onset is not obviously false. For example, the percentage increase in diagnosis of heart conditions among the continuously uninsured is 35.6%, compared to an increase of 42.5% among the continuously insured. The percentage change in cancer diagnoses is 36.0% among the uninsured and 42.5% among the insured. Similar percentage changes are observed for all of the other conditions, with the exception of lung conditions. In that case, the percentage increase is only 10.2% for the uninsured, but 46.2% among the insured. Because lung conditions such as emphysema and chronic bronchitis often have obvious outward symptoms such as coughing or difficulty breathing, it is not clear why the rate of new onset would be so much higher among the insured. A more formal test of this assumption was performed by running similar models to that in (3), but using arbitrary years in the waves prior to Medicare as the $medicare_{it}$ variable. If this assumption holds, there should be no differential rate of new diagnosis by prior insurance status. This, in fact, was found to be the case for every condition considered. The similar rates of change prior to Medicare found both descriptively and analytically suggest that the underlying assumption that the uninsured and insured would have similar onset rates, all else equal, is satisfied.

To give some indication of the importance of the magnitude of the discovery effect, Table 3 consists of two-way tables of insurance status and time period for each health condition in the wave before Medicare and the wave after Medicare by gender. For most, this corresponds to ages 63 and 67 respectively.[21] The difference-in-differences estimates indicate the additional percentage point increase in diagnosis for the continuously uninsured relative to the continuously insured around the time of Medicare. For both men and women, the majority of these difference-in-differences estimates are positive, indicating that new diagnoses occur at a faster rate for the uninsured after Medicare and that the discovery effect may be quite important. However, for

[21] Because of the fact that HRS interviews could be conducted on someone's 65th birthday, before care could have been obtained by Medicare, the wave after the Medicare wave is better to study changes in health status. However, for others, their first HRS interview after Medicare enrollment would have occurred closer to age 67, so that they would have had longer to obtain diagnosis. Age controls will be included in the hazard models to account for this difference.

men the results are much closer to zero in many cases than for women, suggesting that uninsured women may be more likely to have postponed medical care for undiagnosed conditions. While these results are suggestive of the important role of the discovery effect after Medicare enrollment, health status is influenced by a number of factors, and thus models which can adequately control for covariates are necessary.

3. Results from Cox Relative Risk Models

3.1. Diagnosis of New Conditions, by Gender

Table 4 presents the estimated hazard ratios for the coefficients of interest from Equation (3) (Medicare, insurance status, and Medicare-insurance status interactions). Robust standard errors and corresponding z-statistics are also presented. These models were estimated separately for men and women as opposed to performing a single stratified model because men and women may face different baseline as well as ongoing hazards for various conditions. There is a separate table for each of six health conditions; the models for stroke could not be estimated due to the small number of failures by stroke in the previously uninsured group once enrolled on Medicare. Each condition presents results from two specifications. The first (I), controls only for demographic and economic characteristics, measured from the previous HRS interview. The second (II) specification builds on that in (I) and adds in the health measures previously described.

Tables 4a-4e show that the diagnosis effect is important for most of the health conditions considered. The diagnosis effect implies that the rate of diagnosis prior to Medicare will be lower for the uninsured compared to the insured. One would expect that the diagnosis effect in the years prior to Medicare would be quite large for heart conditions, lung conditions, diabetes and cancer because these conditions are hard to self-diagnose and may be asymptomatic. For these conditions, the expectation is that the coefficient on uninsurance and intermittently insured would be less than one, which corresponds to the hazard ratio among the continuously insured prior to Medicare. With the exception of women with diabetes and men with cancer, this expectation holds and the hazard ratio is far less than one. There is some variation in the magnitude of these coefficients, but in general, the relative risk of diagnosis prior to Medicare is much lower among the continuously uninsured than the insured. Though hypertension is generally asymptomatic, high blood pressure is something that may be more easily caught be the uninsured through the use of home monitoring systems or machines commonly available in drug stores and pharmacies. Because of the easier ability to obtain a diagnosis due to readily available testing, the hazard ratios on the insurance coefficients for hypertension are close to one for the previously uninsured, suggesting that the relative risk of failure is about the same prior to Medicare, regardless of insurance coverage.

The results in Table 4 also indicate the importance of the discovery effect, which implies that the rate of new diagnosis should be larger for those who were previously uninsured. There is evidence of a weak discovery effect among the continuously insured group, as indicated by a coefficient larger than one on the Medicare variable. This may be due to more generous coverage from Medicare for diagnostic tests compared to prior private insurance. Though many individuals have insurance coverage, they are often underinsured and therefore may not have as easy access to care for all needed procedures (Schoen et al., 2005). Results also show strong evidence of a discovery effect among the continuously uninsured for most conditions. The change in the hazard ratio of new heart conditions after Medicare for uninsured men is 4.3 times bigger than for insured men, the corresponding number for women is only about 1.14. The differential increase in hazard ratios for lung conditions after Medicare among the continuously uninsured are between 85% and 145% larger for men and 227-262% larger for women. There is also slight increase in the hazard of diagnosis of high blood pressure at age 65 for the continuously insured; the differential risk of failure for the previously uninsured is about 28-37% higher for men and approximately 32-37% higher for women. Continuously uninsured men have an additional increase in the hazard ratio of diagnosis of diabetes after Medicare that is more than 100% higher than insured men, while the differential hazard for uninsured women is about 37% higher. Continuously uninsured women are approximately 290% more likely to be diagnosed with cancer after obtaining Medicare than those who previously had insurance coverage prior to Medicare, but men do not show any evidence of a discovery effect for cancer.

The case of arthritis is somewhat different that the others, largely owing to the way to the way the diagnosis condition is asked in the HRS. Unlike the other conditions which only ask about doctor's diagnoses, this question allows individuals to respond whether they have arthritis or rheumatism, or whether a doctor has ever told them that they do. Thus, individuals are free to self-diagnose the condition based on their symptoms. Thus, one would expect that there would be little evidence of a diagnosis or discovery effect, as individuals are free to diagnose themselves at any point. This is precisely what is shown in the coefficient estimates. For women, the hazard ratio on both the uninsurance and uninsurance-Medicare variables are approximately one, suggesting little difference by insurance status. For men, the coefficient on the insurance interaction is also approximately one, but the hazard ratio on the uninsurance term is greater than one. Because there is little evidence of either the diagnosis or discovery effect for a condition that does not require a doctor's diagnosis, this stands as somewhat of a consistency check on the hypotheses previously presented.

Figure 1 illustrates the pre-Medicare and post-Medicare hazard rates for the previously uninsured and insured groups using the results estimated from specification (II) in Table 4. The reference group, the continuously insured prior to Medicare have a hazard rate of 1 until Medicare. After Medicare, their hazard rate becomes $\exp(\beta_3)$, or the coefficient on Medicare in Table 4. The previously uninsured prior to Medicare have a relative risk of $\exp(\beta_4)$, the hazard ratio reported for the continuously uninsured in Table 4. The hazard ratio of the previously uninsured after Medicare is $\exp(\beta_3+\beta_4+\beta_6)$, or the product of the Medicare, continuously uninsured, and Medicare-uninsurance interaction terms reported in Table 4. There is no clear pattern that emerges for every one of these conditions, but both the uninsured and the insured experience increases in the hazard of diagnosis once enrolled on Medicare for many of the conditions. In most cases though, the hazard rate of diagnosis for the uninsured after Medicare does not even reach the hazard of diagnosis for the insured prior to Medicare. Though there is no clear pattern that holds for each of these graphs, they support both the diagnosis effect (the hazard of the uninsured is lower than the insured prior to Medicare) and the discovery effect (the increase in the hazard at age 65 in many cases is larger for those who previously lacked insurance than for those who had coverage).

3.2. Diagnosis of New Conditions, Men and Women Combined

Table 5 contains aggregate results for the diagnosis of particular conditions and for the diagnosis of any new chronic conditions at all. In the first 6 columns, results are reported by condition, but both men and women are included in the model. The main reason to combine the genders is to increase sample size; in many cases in Table 4, the actual magnitude of the hazard ratios is different by gender, but both genders move in the same direction and the hypothesis that they are equal cannot be rejected. All of the control variables are interacted with gender because there may be different effects of education, socioeconomic status, and self-rated health measures on the decision to seek medical treatment and on the onset of conditions. The general pattern of coefficients in these interacted models is the same as before: the diagnosis effect leads to lower hazard rates among the previously uninsured prior to Medicare (for all conditions except arthritis) and the discovery effect leads to a higher relative hazard rate after Medicare for the previously uninsured relative to the insured. When both genders are included, the results indicate that many of the predictions laid out earlier are satisfied. The differential hazard rates after Medicare enrollment are lower for conditions that can be self-diagnosed (arthritis due to the HRS question wording and high blood pressure due to readily available diagnostic tests at pharmacies and drug stores) and the highest hazard rates are observed for conditions that may not have obvious outward symptoms (heart condition, cancer) or harder to self-diagnose (lung condition, cancer). However, none of these uninsured-Medicare interaction coefficients are statistically significantly different from a hazard ratio of 1.

In the final column of Table 5, all health conditions excluding arthritis are combined into one summary measure of "any new diagnosis." This model again includes both genders and interacts all other covariates with gender. By defining the variable in this way, the risk set becomes somewhat less obvious because someone who was diagnosed with high blood pressure 20 years prior to Medicare will be excluded from the risk set, even if receiving a diagnosis of a heart condition very soon after Medicare enrollment. In other words, this model does not do a good job at controlling for correlation between health conditions, but is rather meant to provide a summary measure of whether overall there is evidence of the diagnosis or discovery effect. In fact, the coefficients in the summary measure model look quite similar to those for individual conditions: the hazard ratio of the uninsured prior to Medicare is lower than one (diagnosis effect) and is about 40% higher than the previously insured after Medicare (discovery effect). Despite the consistent findings by condition and overall, the hypothesis that these coefficients are different from one cannot be rejected.

Instead of defining Medicare as a single binary variable, an alternative is to define an additional dummy variable for the first two years of Medicare. In this specification, one variable captures whether the individual was covered by Medicare in that wave, the other is an additional dummy for the first two interview waves reporting Medicare.[22] The purpose for this is to capture the short-term discovery effect; Schimmel (2005) found that there was an initial spike in utilization in the first two waves of Medicare enrollment. If this increased utilization is what

[22] For those who first turned 65 in 2002, only the first wave of Medicare data is currently available.

leads to the discovery of new conditions, we would expect it to happen in the first few years of coverage as opposed to 6 years after enrollment on Medicare. Thus, this measure may in fact be a cleaner measure of the discovery effect owing to new insurance coverage via Medicare. The interpretation of the coefficients here is much the same as before, the exception being that the get the overall hazard ratio for the first two periods of Medicare enrollment, one must multiply the coefficient on Medicare and the first two waves of Medicare. A coefficient of larger than one on the first two waves on Medicare (and interaction term) indicates that the differential hazard is larger in the first two periods, which is what is predicted by the discovery effect. Table 6 reports these results, again combined by gender.[23]

Though most of the coefficients on the uninsurance-Medicare interaction terms are not significantly different from one, the point estimates are consistent with the discovery effect. In every case, the coefficient on the interaction term between continuously uninsured and the first two periods on Medicare is larger than one, indicating that the differential rate of diagnosis among the uninsured is higher in the initial period enrolled on Medicare than later. In fact, the coefficient the interaction between uninsurance and overall Medicare enrollment in many cases is less than one, suggesting that the majority of the discovery effect occurs within the first few years of Medicare enrollment. These coefficients for the previously insured show little evidence of the discovery effect, as the coefficients in the first two waves on Medicare are generally less than one, while the overall Medicare coefficient is usually larger than but close to one. Though these results are not precise, the correspondence of the increased diagnosis here to the increased utilization found in early waves of Medicare enrollment in Schimmel (2005) suggests that the discovery effect is largely responsible for the higher rate of diagnosis after Medicare enrollment among the previously uninsured.

Several other robustness checks using alternative definitions of insurance coverage were performed to confirm the consistency of the previously reported estimates. First, instead of using insurance status in the two waves prior to Medicare, one-period uninsurance from the wave immediately prior to Medicare enrollment was considered. The results in this case were as expected. Though the basic pattern of coefficients remained, the coefficients on uninsurance and on the uninsurance-Medicare interaction were smaller in magnitude than when considering the

[23] Because of the small number of failures in certain time periods when looking separately by gender, these results have been aggregated so that models can be estimated. Intermittently insured is also included as a separate category, but only the uninsurance and uninsurance-Medicare interaction terms are reported in this table.

two-period measure. This is because the one-period measure combines the continuously uninsured and the intermittently uninsured; the latter group less likely to experience the diagnosis effect due to intermittent access to medical care. Results also demonstrated the same pattern of coefficients (but lacked statistical significance) when the two-period measure of uninsurance was aggregated to “any uninsurance in two periods” instead of the continuously uninsured and intermittently uninsured. Like the previous modification to the model, the coefficient magnitudes on uninsurance were smaller because the intermittently covered group was combined with the continuously uninsured. Finally, pre-Medicare insurance status in the wave prior to Medicare was then broken down into employer-sponsored, public (Champus or Medicaid), and privately purchased and the models were re-run comparing results by insurance status. There was no significant difference between insurance groups, though in some cases the hazard ratio of the previously uninsured relative to those covered by an employer were stronger than when compared to the entire group of the insured. Nonetheless, the pattern of coefficients evidencing the diagnosis and discovery effect remained.

4. Discussion of Results and Conclusions

Though the uninsured generally have lower levels of diagnosis of chronic conditions relative to the insured, once insurance coverage becomes available via Medicare at age 65, the uninsured experience larger increases in the rate of new diagnoses. These increases occur despite the fact that rate of diagnosis is about the same in the years prior to Medicare, regardless of insurance status. Although the uninsured appear to be healthier on the score of chronic conditions prior to age 65, the increased diagnosis immediately upon receipt of Medicare coverage indicates an underdiagnosis of chronic conditions among the uninsured. The increased diagnoses for virtually every chronic condition in conjunction with the timing of the new diagnoses close to Medicare enrollment, indicates the importance of the discovery effect in explaining the differential changes. The real importance of the discovery effect lies in the fact that many of these conditions were present prior to the availability of medical care, meaning that the lack of contact with the medical system while uninsured led to the delay of proper treatment and timely care of chronic conditions. For most of the chronic conditions considered here, delay of medical care could lead to a worsening of symptoms or be fatal if the condition is not caught in time.

One important issue with the results in this paper is the small sample size and number of failures with which to estimate these models. The lack of sample size led to imprecisely estimated coefficients for the models that could be estimated and also caused the inability to estimate the Cox model for the diagnosis of a stroke. However, this problem may only be temporary, as data from the 2004 wave of the Health and Retirement Study will soon be available. The advantage of this data is twofold. First, an additional wave of failures will be available for the 1996-2002 sample years already included in the analyses here. This will be particularly relevant for the later cohorts, as data in years close to Medicare enrollment can be added. Second, an additional sample year of data will be available for those who first were observed enrolling on Medicare above the age of 65 in 2004. This will add approximately 1,000 observations to a current sample size of slightly more than 3,000. These data will increase the precision of the estimates and allow for the separation of the intermittently insured group into two categories (uninsured-then-insured and insured-then-uninsured).

Once the significance of the coefficient patterns can be confirmed with the 2004 HRS data, additional work can be pursued. First, it may be possible to look at disease severity in the HRS using information about medication and physician use in relation to the diagnosis of conditions. Unfortunately these questions have changed across HRS interviews, making cross-wave comparisons difficult. Also, it is not clear if someone who takes medication has a more severe form of a condition than someone who does not, as it may instead reflect better disease management due to more access to medical care. Even despite these difficulties, additional exploration may be warranted. One goal of this future work would be to use the increased rate of diagnosis after 65 to calculate a conversion factor that would relate the observed level of diagnosis prior to Medicare enrollment to the true underlying level of illness in the population. Newly available data from the English Longitudinal Study on Ageing (ELSA) may be advantageous for this purpose, as health insurance in the United Kingdom does not have an automatic break in coverage at age 65. These analyses together could help provide a better picture of the ways in which uninsurance affects health status and the diagnosis of conditions.

The delayed treatment of chronic conditions in order to restore health can lead to much more costly interventions once medical care is available. Consider the case of diabetes. If caught in the early stages, it may be treated by diet and exercise modification or by the use of insulin. However, if care is delayed for a long period, by the time treatment is available, additional related issues such as podiatric, vision, or cardiovascular problems could also be involved. A similar argument could be made for many other chronic conditions. As health insurance reform is debated in the United States, it is important to maintain a focus on the intertemporal importance of health insurance and access to medical care. The original HMOs recognized that early intervention could reduce the overall cost of treatment, and this remains the case. The results here and in Schimmel (2005) stress the importance of the continuity of health insurance in the years prior to Medicare enrollment (when a number of health conditions begin to occur) as a way to maintain access to medical care, increase timely diagnosis of conditions, and ultimately improve health outcomes.

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Table 1a: Descriptive Statistics at Baseline HRS Interview in 1992- Men Only

	Continuously uninsured n=120	**Intermittently insured** n=194	**Continuously insured** n=1,214		**Continuously uninsured** n=120	**Intermittently insured** n=194	**Continuously insured** n=1,214
Age (years)	58.21	58.28	58.11	Self-rated health	3.365	3.603	3.777
	1.82	*1.88*	*1.97*	*(1=poor, 5=excellent)*	*1.235*	*1.079*	*1.003*
Education- Less than high school	0.423	0.270	0.150	Diagnosed chronic conditions*	0.610	0.582	0.607
	0.496	*0.445*	*0.357*	*(min=0, max=6)*	*0.736*	*0.791*	*0.719*
Education- High school graduate	0.174	0.224	0.305	Smoke ever	0.759	0.677	0.712
	0.380	*0.418*	*0.461*		*0.429*	*0.469*	*0.453*
Education- Some college	0.153	0.171	0.202	Currently smoke	0.375	0.207	0.186
	0.362	*0.377*	*0.401*		*0.486*	*0.406*	*0.389*
Education- College graduate	0.131	0.260	0.282	Currently drink	0.687	0.709	0.727
	0.338	*0.440*	*0.450*		*0.466*	*0.455*	*0.446*
Census region- Northeast	0.145	0.187	0.195	Father living	0.091	0.133	0.145
	0.353	*0.391*	*0.396*		*0.289*	*0.340*	*0.353*
Census region- Midwest	0.160	0.205	0.271	Mother living	0.341	0.386	0.347
	0.368	*0.405*	*0.444*		*0.471*	*0.487*	*0.477*
Census region- South	0.448	0.328	0.346	Body mass index- overweight	0.451	0.539	0.524
	0.499	*0.471*	*0.476*	*25.0-29.9*	*0.500*	*0.500*	*0.500*
Black	0.150	0.098	0.059	Body mass index- obese	0.208	0.160	0.206
	0.359	*0.299*	*0.235*	*30 or greater*	*0.407*	*0.368*	*0.404*
Hispanic	0.177	0.072	0.030	No functional limitations	0.684	0.704	0.714
	0.384	*0.259*	*0.172*		*0.467*	*0.458*	*0.452*
Married	0.633	0.845	0.849	More than one functional limitation	0.167	0.119	0.113
	0.484	*0.362*	*0.358*		*0.374*	*0.324*	*0.316*
Currently working for pay	0.761	0.841	0.828	Percent with 1-5 ADL difficulties	0.964	0.988	0.985
	0.428	*0.366*	*0.377*		*0.188*	*0.107*	*0.123*
Say that fully/partially retired	0.155	0.217	0.217	Percent with 1-3 IADL difficulties	0.835	0.896	0.921
	0.363	*0.414*	*0.412*		*0.372*	*0.306*	*0.270*
Annual household income	28.58	60.25	60.48	CESD Score = 0	0.603	0.691	0.744
($1,000s)	*33.10*	*71.93*	*54.22*		*0.491*	*0.463*	*0.436*
Household wealth	182.99	304.99	311.50	CESD Score = 4-8	0.029	0.007	0.010
($1,000s)	*366.32*	*501.01*	*562.25*		*0.168*	*0.082*	*0.099*

All measures from the 1992 baseline interview
Weighted using 1992 person-level weights
Standard deviations in italics
* Excludes arthritis since not limited to doctor diagnosis

Table 1b: Descriptive Statistics at Baseline HRS Interview in 1992- Women Only

	Continuously uninsured	**Intermittently insured**	**Continuously insured**		**Continuously uninsured**	**Intermittently insured**	**Continuously insured**
	n=183	n=248	n=1,433		n=183	n=248	n=1,433
Age (years)	57.95	58.16	58.02	Self-rated health	3.224	3.441	3.698
	1.91	*1.99*	*1.92*	*(1=poor, 5=excellent)*	*1.176*	*1.134*	*1.045*
Education- Less than high school	0.468	0.308	0.159	Diagnosed chronic conditions*	0.695	0.599	0.577
	0.500	*0.463*	*0.366*	*(min=0, max=6)*	*0.910*	*0.821*	*0.762*
Education- High school graduate	0.307	0.330	0.412	Smoke ever	0.537	0.564	0.521
	0.463	*0.470*	*0.492*		*0.500*	*0.497*	*0.500*
Education- Some college	0.113	0.158	0.210	Currently smoke	0.306	0.245	0.203
	0.317	*0.366*	*0.407*		*0.462*	*0.431*	*0.402*
Education- College graduate	0.060	0.157	0.178	Currently drink	0.405	0.523	0.623
	0.239	*0.364*	*0.383*		*0.492*	*0.500*	*0.485*
Census region- Northeast	0.150	0.228	0.218	Father living	0.113	0.093	0.116
	0.358	*0.420*	*0.413*		*0.317*	*0.291*	*0.320*
Census region- Midwest	0.154	0.232	0.298	Mother living	0.330	0.300	0.350
	0.362	*0.423*	*0.458*		*0.472*	*0.459*	*0.477*
Census region- South	0.467	0.357	0.296	Body mass index- overweight	0.390	0.347	0.350
	0.500	*0.480*	*0.456*	*25.0-29.9*	*0.489*	*0.477*	*0.477*
Black	0.162	0.137	0.065	Body mass index- obese	0.299	0.204	0.201
	0.370	*0.344*	*0.246*	*30 or greater*	*0.459*	*0.404*	*0.401*
Hispanic	0.143	0.072	0.028	No functional limitations	0.421	0.508	0.555
	0.351	*0.260*	*0.164*		*0.495*	*0.501*	*0.491*
Married	0.633	0.606	0.760	More than one functional limitation	0.394	0.322	0.239
	0.483	*0.490*	*0.427*		*0.490*	*0.468*	*0.427*
Currently working for pay	0.501	0.566	0.635	No ADL difficulties	0.943	0.963	0.984
	0.501	*0.497*	*0.482*		*0.232*	*0.183*	*0.125*
Say that fully/partially retired	0.200	0.208	0.191	No IADL difficulties	0.697	0.784	0.810
	0.401	*0.407*	*0.394*		*0.461*	*0.413*	*0.393*
Annual household income	22.39	35.22	50.55	CESD Score = 0	0.531	0.624	0.700
($1,000s)	*22.29*	*33.37*	*51.07*		*0.500*	*0.483*	*0.458*
Household wealth	109.17	191.81	289.88	CESD Score = 4-8	0.099	0.067	0.038
($1,000s)	*240.90*	*301.59*	*461.26*		*0.299*	*0.251*	*0.192*

All measures from the 1992 baseline interview
Weighted using 1992 person-level weights
Standard deviations in italics
* Excludes arthritis since not limited to doctor diagnosis

Table 2: Diagnosis Levels at Baseline HRS Interview in 1992 and by 2002 Interview, By Gender

	Men				Women			
	Total n=1,528	Coninuously uninsured n=120	Intermittently insured n=194	Continuously insured n=1,214	Total n=1,864	Coninuously uninsured n=183	Intermittently insured n=248	Continuously insured n=1,433
Percentage with Various Chronic Conditions at Baseline 1992 HRS Interview								
Heart condition	11.09	5.20	9.99	11.73	7.26	6.84	8.61	7.09
Lung condition	3.40	7.77	2.56	3.18	4.42	7.32	4.80	4.06
High blood pressure	34.34	34.36	29.87	35.01	32.28	37.33	29.63	32.18
Diabetes	7.31	11.06	8.71	6.80	6.40	8.79	7.69	5.95
Arthritis	28.38	26.41	23.16	29.33	41.23	39.80	44.54	40.86
Cancer	2.49	0.00	4.06	2.46	7.25	6.47	7.92	7.23
Stroke	1.76	2.59	3.02	1.51	1.33	2.75	1.20	1.21
Percentage with Various Chronic Conditions by 2002 HRS Interveiw								
Heart condition	27.45	19.64	25.93	28.30	18.50	21.14	18.04	18.30
Lung condition	8.81	12.93	6.46	8.83	10.65	13.15	13.66	9.91
High blood pressure	52.83	46.28	48.62	53.99	53.77	55.23	53.60	53.64
Diabetes	18.61	21.97	19.24	18.24	15.08	26.77	18.09	13.40
Arthritis	55.60	61.32	51.14	55.81	67.31	66.94	69.48	67.00
Cancer	14.45	17.97	17.19	13.75	14.38	14.49	17.16	13.92
Stroke	6.56	6.12	7.42	6.46	5.70	8.84	5.09	5.47

Weighted using 1992 person-level weights

Table 3a: Mean Difference-in-Differences in the Diagnosis of Conditions between Wave Before and Wave After Medicare, Men Only

Heart condition

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	6.64	16.43	9.79
Cont. insured	19.20	26.37	7.17
Uninsured-insured	-12.56	-9.94	2.62

Stroke

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	3.54	5.90	2.36
Cont. insured	2.67	4.95	2.28
Uninsured-insured	0.87	0.95	0.08

Lung condition

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	7.84	9.28	1.44
Cont. insured	5.96	6.36	0.40
Uninsured-insured	1.88	2.92	1.04

Cancer

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	5.07	17.58	12.51
Cont. insured	7.31	12.89	5.58
Uninsured-insured	-2.24	4.69	6.93

High blood pressure

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	38.15	42.69	4.54
Cont. insured	40.85	51.14	10.29
Uninsured-insured	-2.70	-8.45	-5.75

Arthritis

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	43.41	59.39	15.98
Cont. insured	43.69	54.65	10.96
Uninsured-insured	-0.28	4.74	5.02

Diabetes

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	16.73	22.66	5.93
Cont. insured	10.67	16.36	5.69
Uninsured-insured	6.06	6.30	0.24

Weighted using 1992 person-level weights

Those who turned 65 in 2002 are excluded because of the lack of data in the wave after Medicare

Table 3b: Mean Difference-in-Differences in the Diagnosis of Conditions between Wave Before and Wave After Medicare, Women Only

Heart condition

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	15.57	25.31	9.74
Cont. insured	13.10	17.79	4.69
Uninsured-insured	2.47	7.52	5.05

Stroke

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	5.74	10.05	4.31
Cont. insured	1.88	4.89	3.01
Uninsured-insured	3.86	5.16	1.30

Lung condition

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	11.34	17.10	5.76
Cont. insured	6.34	8.30	1.96
Uninsured-insured	5.00	8.80	3.80

Cancer

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	5.73	13.90	8.17
Cont. insured	10.97	13.88	2.91
Uninsured-insured	-5.24	0.02	5.26

High blood pressure

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	44.13	58.55	14.42
Cont. insured	41.21	50.55	9.34
Uninsured-insured	2.92	8.00	5.08

Arthritis

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	56.47	65.92	9.45
Cont. insured	55.46	64.48	9.02
Uninsured-insured	1.01	1.44	0.43

Diabetes

	Wave before Medicare	Wave after Medicare	After-Before
Cont. uninsured	10.92	23.32	12.40
Cont. insured	9.31	13.45	4.14
Uninsured-insured	1.61	9.87	8.26

Weighted using 1992 person-level weights

Those who turned 65 in 2002 are excluded because of the lack of data in the wave after Medicare

Table 4a: Cox Relative Risk Estimation Results, Heart Condition

	Men		Women	
	I	**II**	**I**	**II**
Medicare	**0.5983**	**0.5604**	**1.1428**	**1.1335**
	0.1449	*0.1366*	*0.3124*	*0.3173*
	-2.12	-2.38	0.49	0.45
Continuously uninsured	**0.4394**	**0.4128**	**0.8607**	**0.7717**
	0.2229	*0.2021*	*0.2998*	*0.2677*
	-1.62	-1.81	-0.43	-0.75
Intermittently insured	**0.4898**	**2.8485**	**0.5933**	**0.6026**
	0.1899	*1.6798*	*0.2220*	*0.2251*
	-1.84	1.78	-1.40	-1.36
Unins.-Medicare interaction	**2.5746**	**2.9326**	**1.4071**	**1.2680**
	1.5597	*1.6798*	*0.5865*	*0.5399*
	1.56	1.78	0.82	0.56
Int. ins.-Medicare interaction	**2.5848**	**2.9326**	**1.3107**	**1.3237**
	1.1887	*1.4258*	*0.6146*	*0.6202*
	2.06	2.21	0.58	0.60
Log likelihood	-1515.23	-1450.39	-1511.15	-1461.44
Number of observations	5731	5565	7929	7774
Number of individuals	1331	1319	1717	1712
Number of failures	218	212	210	207
All Medicare waves	X	X	X	X
Health controls included		X		X

Estimated using robust standard errors clustered at the individual level, Breslow method for approximating exact marginal probability

Coefficients in bold, standard errors in italics, t-statistics in normal font

Table 4b: Cox Relative Risk Estimation Results, Lung Condition

	Men		Women	
	I	**II**	**I**	**II**
Medicare	**1.2724**	**1.1099**	**0.7301**	**0.6726**
	0.5336	*0.4645*	*0.2562*	*0.2411*
	0.57	0.25	-0.90	-1.11
Continuously uninsured	**0.2068**	**0.1327**	**0.3831**	**0.3010**
	0.2080	*0.1365*	*0.2326*	*0.1823*
	-1.57	-1.96	-1.58	-1.98
Intermittently insured	**0.1710**	**0.1327**	**1.1819**	**0.9954**
	0.1737	*0.1352*	*0.4156*	*0.3564*
	-1.74	-1.98	0.48	-0.01
Unins.-Medicare interaction	**2.4441**	**1.8521**	**3.2736**	**3.6285**
	2.8757	*2.3499*	*2.3333*	*2.6274*
	0.76	0.49	1.66	1.78
Int. ins.-Medicare interaction	**4.6045**	**4.4110**	**1.1915**	**1.3774**
	5.0663	*4.8471*	*0.5890*	*0.6888*
	1.39	1.35	0.35	0.64
Log likelihood	-518.61	-464.57	-851.68	-804.04
Number of observations	6429	6248	8341	8177
Number of individuals	1441	1431	1780	1773
Number of failures	76	73	117	115
All Medicare waves	X	X	X	X
Health controls included		X		X

Estimated using robust standard errors clustered at the individual level, Breslow method for approximating exact marginal probability

Coefficients in bold, standard errors in italics, t-statistics in normal font

Table 4c: Cox Relative Risk Estimation Results, High Blood Pressure

	Men		Women	
	I	II	I	II
Medicare	**1.2376**	**1.2355**	**1.1187**	**1.0574**
	0.2762	*0.2763*	*0.2098*	*0.1983*
	0.96	0.94	0.60	0.30
Continuously uninsured	**0.4082**	**0.4455**	**0.6743**	**0.6355**
	0.2116	*0.2339*	*0.1958*	*0.1848*
	-1.73	-1.54	-1.36	-1.56
Intermittently insured	**1.0469**	**1.0992**	**0.9150**	**0.8899**
	0.2677	*0.2948*	*0.2053*	*0.1975*
	0.18	0.35	-0.40	-0.53
Unins.-Medicare interaction	**1.3773**	**1.2763**	**1.3767**	**1.3225**
	0.8597	*0.8004*	*0.5052*	*0.4893*
	0.51	0.39	0.87	0.76
Int. ins.-Medicare interaction	**0.6768**	**0.5911**	**0.9275**	**0.9857**
	0.2269	*0.2064*	*0.2643*	*0.2793*
	-1.16	-1.51	-0.26	-0.05
Log likelihood	-1742.39	-1679.83	-2692.46	-2601.17
Number of observations	4013	3892	5291	5192
Number of individuals	972	961	1221	1217
Number of failures	264	257	391	383
All Medicare waves	X	X	X	X
Health controls included		X		X

Estimated using robust standard errors clustered at the individual level, Breslow method for approximating exact marginal probability

Coefficients in bold, standard errors in italics, t-statistics in normal font

Table 4d: Cox Relative Risk Estimation Results, Diabetes

	Men		Women	
	I	**II**	**I**	**II**
Medicare	**1.6397**	**1.6199**	**1.3561**	**1.5301**
	0.4683	*0.4730*	*0.3808*	*0.4284*
	1.73	1.65	1.08	1.52
Continuously uninsured	**0.5288**	**0.4351**	**1.0003**	**0.9634**
	0.2900	*0.2691*	*0.3439*	*0.3409*
	-1.16	-1.35	0.00	-0.11
Intermittently insured	**0.7114**	**0.6690**	**1.0858**	**1.3280**
	0.2636	*0.2831*	*0.3695*	*0.4418*
	-0.92	-0.95	0.24	0.85
Unins.-Medicare interaction	**2.0643**	**2.3445**	**1.4062**	**1.3735**
	1.2689	*1.6192*	*0.5810*	*0.5701*
	1.18	1.23	0.83	0.76
Int. ins.-Medicare interaction	**1.3399**	**1.5723**	**1.1429**	**1.1120**
	0.6397	*0.8177*	*0.4829*	*0.4607*
	0.61	0.87	0.32	0.26
Log likelihood	-1172.51	-1095.76	-1215.39	-1115.11
Number of observations	5961	5797	8033	7887
Number of individuals	1374	1364	1724	1719
Number of failures	168	163	170	166
All Medicare waves	X	X	X	X
Health controls included		X		X

Estimated using robust standard errors clustered at the individual level, Breslow method for approximating exact marginal probability
Coefficients in bold, standard errors in italics, t-statistics in normal font

Table 4e: Cox Relative Risk Estimation Results, Cancer

	Men		Women	
	I	II	I	II
Medicare	**1.1925**	**1.2123**	**0.6295**	**0.6027**
	0.3498	*0.3624*	*0.2115*	*0.2027*
	0.60	0.64	-1.38	-1.51
Continuously uninsured	**1.7776**	**1.5296**	**0.4591**	**0.4589**
	0.7026	*0.6377*	*0.2694*	*0.2698*
	1.46	1.02	-1.33	-1.32
Intermittently insured	**0.9478**	**0.8586**	**0.9539**	**0.9531**
	0.3808	*0.3681*	*0.3629*	*0.3621*
	-0.13	-0.36	-0.12	-0.13
Unins.-Medicare interaction	**0.8175**	**0.9744**	**3.7467**	**3.8975**
	0.4205	*0.5127*	*0.2559*	*2.6739*
	-0.39	-0.05	1.93	1.98
Int. ins.-Medicare interaction	**1.5143**	**1.6375**	**1.9184**	**1.9602**
	0.7302	*0.8300*	*0.9221*	*0.9409*
	0.86	0.97	1.36	1.40
Log likelihood	-1191.23	-1151.02	-943.42	-918.96
Number of observations	6401	6221	8117	7959
Number of individuals	1462	1451	1732	1727
Number of failures	169	165	130	128
All Medicare waves	X	X	X	X
Health controls included		X		X

Estimated using robust standard errors clustered at the individual level, Breslow method for approximating exact marginal probability

Coefficients in bold, standard errors in italics, t-statistics in normal font

Table 4f: Cox Relative Risk Estimation Results, Arthritis

	Men		Women	
	I	II	I	II
Medicare	**1.3101**	**1.2729**	**0.9812**	**0.9646**
	0.2352	*0.2299*	*0.1640*	*0.1617*
	1.50	1.34	-0.11	-0.21
Continuously uninsured	**1.4651**	**1.4831**	**1.0955**	**1.0792**
	0.3397	*0.3461*	*0.2080*	*0.2060*
	1.65	1.69	0.48	0.40
Intermittently insured	**0.9740**	**0.9181**	**0.9919**	**0.9624**
	0.1850	*0.1863*	*0.1651*	*0.1583*
	-0.14	-0.42	-0.05	-0.23
Unins.-Medicare interaction	**0.9514**	**1.0137**	**1.0317**	**0.9015**
	0.3196	*0.3483*	*0.3012*	*0.2742*
	-0.15	0.04	0.11	-0.34
Int. ins.-Medicare interaction	**1.0608**	**1.1555**	**0.9274**	**0.9807**
	0.2989	*0.3379*	*0.2517*	*0.2660*
	0.21	0.49	-0.28	-0.07
Log likelihood	-2546.07	-2419.77	-3223.26	-3135.58
Number of observations	4161	4039	4133	4068
Number of individuals	1067	1057	1080	1078
Number of failures	380	366	480	472
All Medicare waves	X	X	X	X
Health controls included		X		X

Estimated using robust standard errors clustered at the individual level, Breslow method for approximating exact marginal probability
Coefficients in bold, standard errors in italics, t-statistics in normal font

Table 5: Cox Relative Risk Estimation Results, Men and Women Combined, Health Controls Included

	Heart condition	Lung condition	High blood pressure	Diabetes	Arthritis	Cancer	Any new condition
Medicare	**0.7584**	**0.8402**	**1.1250**	**1.5732**	**1.1067**	**0.8870**	**0.9701**
	0.1398	*0.2306*	*0.1622*	*0.3187*	*0.1358*	*0.1972*	*0.1234*
	-1.50	-0.63	0.82	2.24	0.83	-0.54	-0.24
Continuously uninsured	**0.6065**	**0.2415**	**0.5724**	**0.7374**	**1.2093**	**0.9191**	**0.6735**
	0.1701	*0.1258*	*0.1456*	*0.2194*	*0.1803*	*0.3104*	*0.1332*
	-1.78	-2.73	-2.19	-1.02	1.27	-0.25	-0.20
Intermittently insured	**0.5109**	**0.6172**	**0.9791**	**0.9814**	**0.9557**	**0.9236**	**0.9392**
	0.1407	*0.2108*	*0.1669*	*0.2527*	*0.1218*	*0.2618*	*0.1437*
	-2.44	-1.41	-0.12	-0.07	-0.36	-0.28	-0.41
Unins.-Medicare interaction	**1.7682**	**2.7213**	**1.3023**	**1.6055**	**1.0600**	**1.7206**	**1.3695**
	0.6043	*1.7131*	*0.4111*	*0.5583*	*0.2091*	*0.7060*	*0.3337*
	1.67	1.59	0.84	1.36	0.30	1.32	1.29
Int. ins.-Medicare interaction	**1.9939**	**1.5668**	**0.7988**	**1.2949**	**1.0313**	**1.7168**	**0.8935**
	0.6656	*0.6791*	*0.1754*	*0.4153*	*0.0325*	*0.5924*	*0.0319*
	2.07	1.04	-1.02	0.81	0.98	1.57	-0.28
Log likelihood	-3208.10	-1400.25	-4716.17	-2439.12	-6126.93	-2272.05	-5679.45
Number of observations	13339	14425	9084	13684	8107	14180	6772
Number of individuals	3031	3204	2178	3083	2135	3178	1757
Number of failures	419	188	640	329	838	293	802

Estimated using robust standard errors clustered at the individual level, Breslow method for approximating exact marginal probability

Coefficients in bold, standard errors in italics, t-statistics in normal font

Table 6: Cox Relative Risk Estimation Results, First Two Medicare Waves Separated, Men and Women Combined, Health Controls Included

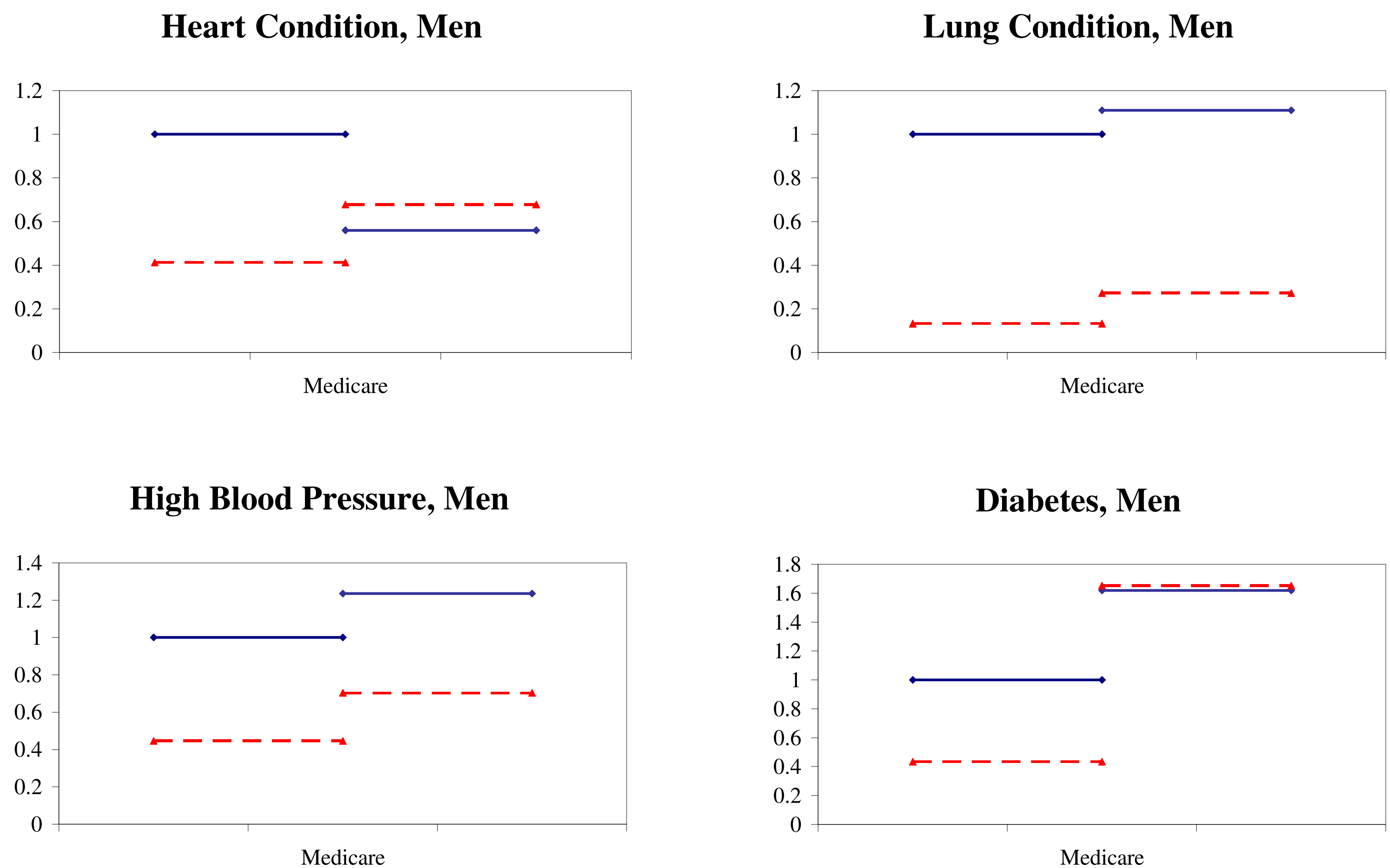
	Heart condition	**Lung condition**	**High blood pressure**	**Diabetes**	**Arthritis**	**Cancer**
First two Medicare waves	**1.0137**	**0.7118**	**0.9700**	**1.0688**	**0.6798**	**1.0712**
	0.2411	*0.2873*	*0.1748*	*0.3309*	*0.1435*	*0.3414*
	0.06	-0.84	-0.17	0.22	-1.83	0.22
Enrolled on Medicare	**0.7319**	**1.1843**	**1.1587**	**1.3709**	**1.6606**	**0.7854**
	0.2427	*0.6522*	*0.3027*	*0.5727*	*0.4597*	*0.3391*
	-0.94	0.31	0.56	0.76	1.83	-0.56
Continuously uninsured	**0.6400**	**0.2509**	**0.5696**	**0.7383**	**1.1887**	**0.9125**
	0.1789	*0.1326*	*0.1435*	*0.2170*	*0.1758*	*0.3036*
	-1.60	-2.62	-2.23	-1.03	1.17	-0.28
Unins.-first two Medicare waves	**1.2499**	**9.5615**	**2.0186**	**1.0794**	**1.5117**	**2.9033**
	0.7020	*4.8194*	*1.4091*	*0.5655*	*0.7191*	*3.0563*
	0.40	4.48	1.01	0.15	0.87	1.01
Unins.-Medicare enrolled interaction	**1.5207**	**0.3826**	**0.7214**	**1.6012**	**0.6943**	**0.6754**
	0.8942	*0.1890*	*0.5182*	*0.8741*	*0.3209*	*0.7249*
	0.71	-1.95	-0.45	0.86	-0.79	-0.37
Log likelihood	-3237.54	-1420.07	-4735.26	-2461.72	-6142.65	-2296.00
Number of observations	13339	14425	9084	13684	8107	14180
Number of individuals	3031	3204	2178	3083	2135	3178
Number of failures	419	188	640	329	838	293

Estimated using robust standard errors clustered at the individual level, Breslow method for approximating exact marginal probability

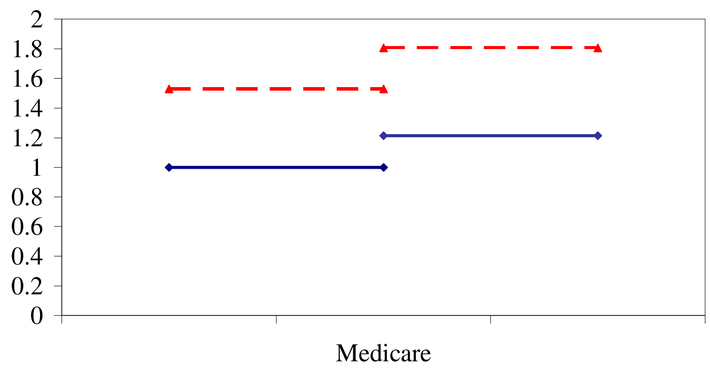
Coefficients in bold, standard errors in italics, t-statistics in normal font

Intermittently insured and interactions included as controls, but not reported here

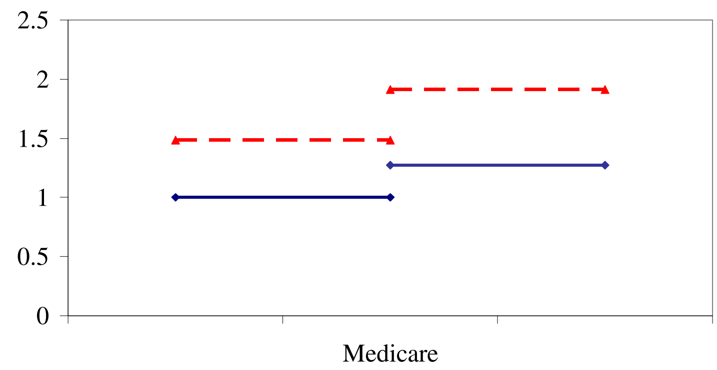
Figure 1a: Estimated Hazard Rates by Insurance Status, Before and After Medicare, Men



Cancer, Men

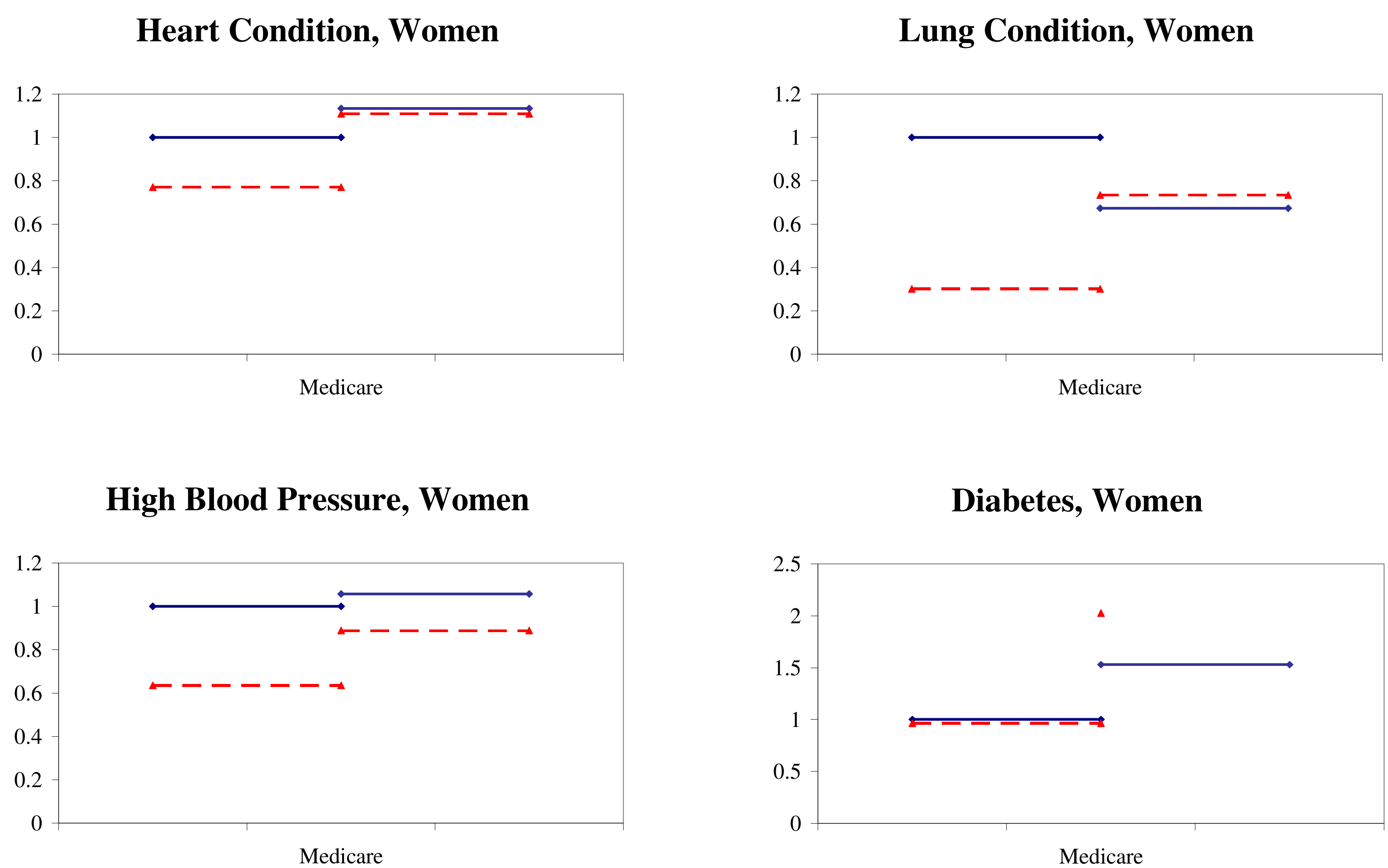


Arthritis, Men

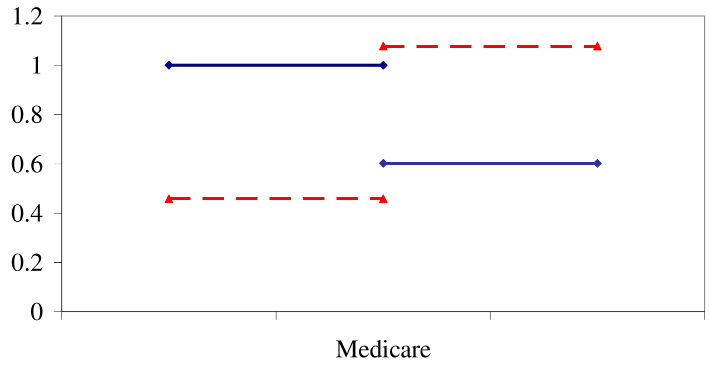


Solid line for continuously insured, dashed line for continuously uninsured, Estimates created using Specification II from Table 4

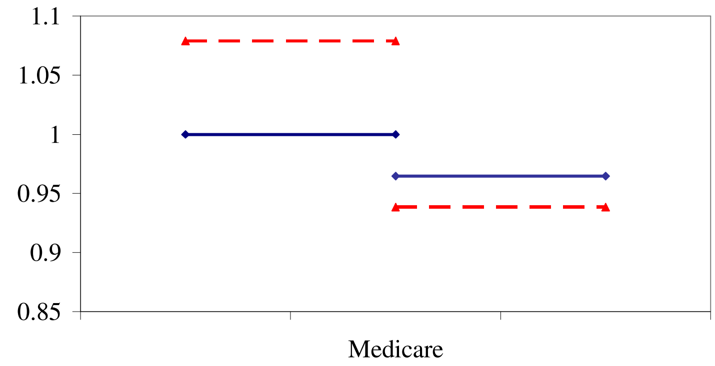
Figure 1b: Estimated Hazard Rates by Insurance Status, Before and After Medicare, Women



Cancer, Women



Arthritis, Women



Solid line for continuously insured, dashed line for continuously uninsured, Estimates created using Specification II from Table 4

Appendix 1: Definition of Health Indices

Self-rated health: Asked on a five-point scale where the possible responses were excellent, very good, good, fair, and poor.

Functional limitations: Sum of binary variables for each of twelve (12) activities in which the respondent reported have "some difficulty" or more. These include: walking several blocks, sitting for two hours, getting up from a chair after sitting, climbing several flights of stairs, stooping/kneeling/crouching, carrying a ten pound object, picking up a dime off of a table, reaching or extending arms, or pulling/pushing a large object.

Activities of daily living: Sum of five (5) binary ADL variables in which a respondent reports having "some difficulty" or more. These include: bathing, dressing, eating, getting into/out of bed, walking across a room.

Instrumental activities of daily living: Sum of three (3) binary IADL variables in which a respondent reports having "some difficulty" or more. At the baseline interview, these include using a map, using a calculator, and using a microwave. Due to differences in questions over time, from 1994 onward, these include using a phone, managing money, and managing medications.

CESD Score: Score measuring the number of depressive symptoms. Sum of binary variables for each of eight (8) symptoms. These include: felt depressed, felt that everything was an effort, had restless sleep, was happy, felt lonely, felt sad, could not get going, enjoyed life.