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Time is Money: Premiums, Coverage, and Outpatient Waiting Times for Elderly Veterans in the United States

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April 29, 2009

Health Care Financing & Economics
U.S. Department of Veterans Affairs
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Abstract

The time spent waiting for an outpatient appointment limits demand in health care delivery systems that do not use financial prices for this purpose. Although outpatient waiting times have been relatively low in the United States, there is reason to believe they may increase in the near future. We estimate models of physician utilization and insurance plan choice for American veterans who were jointly eligible for services from the Veterans Administration (low cost, high waits) and Medicare (higher cost, low waits). We use these models to investigate the financial costs for patients of outpatient waiting times. We find that elderly veterans make very small changes to their utilization patterns and insurance choices in response to changes in outpatient waiting times. We also find that policies that promote access for high-priority veterans seem to reduce the burden of waiting times on the target groups.

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Introduction

In most countries, individuals seeking outpatient care or elective surgery are not always able to get appointments as soon as they would like. Sometimes the wait for the next available appointment is as long as several months. Understandably, these waits are very unpopular and there is a substantial literature on their causes and management (for a recent review, see Cullis, Jones, and Propper, 2000). In general, the literature views wait times as a means of balancing supply and demand when prices are fixed at levels too low to serve this function. In the U.S., health care prices are typically higher and more flexible than in other countries, so waiting times have been relatively low (and the number of uninsured has been high). This may be about to change.

The Obama administration and current leaders in Congress have made a very public commitment to attempt to pass a health care bill that would contain costs and reduce the number of Americans without health insurance (Pear and Stout, 2009). One way these goals could be achieved is to use government authority to restrain prices, a policy that theory suggests might result in increased waiting times. The U.S. Department of Veterans Affairs (VA) is a prominent example of how low prices can lead to waiting times in the American market. The VA provides free or low-cost care to about 4 million veterans every year through a national network of public hospitals and outpatient clinics. Despite recent increases in funding, the VA continues to struggle to manage excess demand for its services, resulting in waiting times as long as 90 days for some services (GAO, 2007). Medicare is a contrasting example. Medicare has established a fee schedule that is lower than most private insurers without increasing waiting times for its beneficiaries (MedPAC, 2009). However, planned reductions in the growth of the fee schedule have been repeatedly postponed by Congress partly because of concern that waiting times would grow if reductions were implemented (MedPAC, 2009).

Even if prices are not restrained, a federal expansion of health insurance could increase waiting times by stimulating demand for services at a time when supply is not expanding. An example of this is Massachusetts, where waiting times for primary care grew to as much as 100 days in the aftermath of a universal health insurance law passed in 2006 (Kowalczyk, 2008).

If waiting times increase in the U.S., welfare will not necessarily decline. In recent theoretical work, Gravelle and Siciliani (2008) showed that waiting times can be used to reduce utilization and the welfare cost of ex post moral hazard if the marginal cost of waiting is inversely related to the benefit of health care. If all patients face the same waits, the marginal cost of waiting should be directly (not inversely) related to the benefit of health care. But all patients do not face the same waits. Most hospitals and clinics already make an effort to accommodate patients who are in need of urgent attention and some managed care organizations and insurance plans promote access to care for selected chronic conditions as part of disease management programs. In addition, physicians typically schedule follow-up appointments based partly on perceived need and patients with established relationships are typically scheduled more promptly than those who are new to a practice.

Given these considerations, how is the marginal cost of waiting related to the benefit of health care in the U.S.? Our goal is to begin to address this question by measuring the marginal cost of waiting among elderly American veterans with a variety of health and demographic characteristics. We focus on elderly veterans because they have access both to the VA health system (with low costs and high waits) and to Medicare-financed care (with higher costs and low waits). Approximately one quarter of elderly Medicare beneficiaries are also veterans and therefore have the opportunity to make this choice. As VA waiting times vary, we can observe the health care financing decisions of these veterans and measure how much they are willing and able to pay to avoid waiting. Holding other factors constant, the amount paid in premiums or out-of-pocket costs by a veteran to avoid a marginal increase in VA waiting times is an estimate of the marginal cost of waiting.

Empirically, we begin by measuring the effect of VA waiting times on the encounter-level choice of VA or Medicare provider for outpatient care. Next, we estimate a model of Medicare plan choice, accounting for the simultaneous determination of plan choice and mix of VA- and Medicare-financed care. Finally, we simulate the effect of a change in VA waiting time on VA-Medicare mix and Medicare plan choice. Our principal data source is the Medicare Current Beneficiary Survey (MCBS) from 2001 through 2003. MCBS contains administrative data from Medicare for eligibility, plan choice, and Medicare utilization and spending. Using a crosswalk available to VA researchers, we link MCBS data to VA administrative data for VA utilization, facility-level waiting times, and distance to VA facilities. We also link county-level data on Medicare plan characteristics from the Medicare Personal Plan Finder database and state-level measures of Medicaid eligibility restrictiveness and Medigap premiums.

Our results indicate that higher VA waiting times induce veterans without disabilities and with middle and higher incomes to use more Medicare-financed care. If high VA waiting times were to persist, our models indicate that these veterans would choose more expensive Medicare health plans, paying more in premiums and more out-of-pocket. By contrast, veterans with low incomes or disabilities are less affected by waiting times, presumably reflecting better access due to the VA priority system.

In the next section we provide some institutional background on the health care financing options available to Medicare-eligible veterans during our study period. Next, we develop a simple conceptual model of veterans' choices and then discuss our statistical specification. We then review our data sources, derive our sample, and present results.

Background

Elderly Americans have many choices about how to finance their healthcare. Traditional fee-for-service Medicare, while universally available, offers coverage that is far from comprehensive. It features high cost-sharing for inpatient and outpatient care and did not generally cover outpatient prescription drugs prior to 2006. To supplement traditional Medicare, beneficiaries can choose among a large number of Medicare HMOs and Medicare supplements (Medigap policies) with varying availability, coverage levels, and premiums (Atherly, 2002). Some beneficiaries may have access to affordable, comprehensive retiree health plans from a former employer. Those with low income and assets may qualify for coverage from Medicaid, although eligibility rules vary from state to state (U.S. House of Representatives, 2004).

Elderly veterans also have the option of seeking care from hospitals and clinics operated by the Veterans Health Administration (VA). The VA is attractive because VA services are comprehensive and inexpensive (there is no insurance premium and co-payments are zero or very low compared to most insurance plans). Unfortunately, VA hospitals and clinics are not conveniently located for each veteran, administration at the VA typically is bureaucratic and slow, and services are not necessarily available when desired (Fortney et al., 2005; GAO, 2007). VA patients often have to wait for weeks or months for the next available appointment and these delays have adverse effects on patient health (Prentice and Pizer, 2007, 2008). To measure the effects of waiting times on beneficiary choices, we focus on veterans who must choose between waiting for care from the VA and higher cost care from Medicare. Consequently, we exclude those who have coverage from Medicaid or employer-sponsored retiree health plans. Our study population first chooses what kind of Medicare coverage they want, and then selects which, if any, services they wish to receive from the VA. In the next section we formalize these choices.

Conceptual Model

We assume that the choice of Medicare plan is made first, at the beginning of the year, and then the decision to seek care from the VA is made on a case-by-case basis throughout the year. These VA-Medicare decisions are analogous to the choice between public and private elective surgery in the U.K., a subject that has received extensive attention in the literature (e.g., Goddard et al., 1994; Besley et al., 1999; Propper, 2000 JHE). Following Lindsay and Feigenbaum (1984), these researchers assume that the value of care decays as time passes between diagnosis and treatment. As a result, the waiting time for public care acts like a price, causing demand to adjust until equilibrium is reached. We begin by adapting these models to the VA-Medicare choice, and then consider how waiting times affect the prior selection of a Medicare plan.

Working backwards, we begin by taking the selection of a Medicare plan as given and consider the individual veteran's choice between VA and Medicare for a particular service. Following the literature, we denote the utility value of treatment delivered when desired by V, p represents the out-of-pocket cost of the Medicare service (relative to other goods), c is the cost of the VA service (including travel time and paperwork), and τ is the Medicare quality premium (mostly from shorter waits but also potentially including more flexibility and other factors). Individuals' place different values on the quality premium because they have different underlying health status, opportunity costs of time, and preferences. This individual valuation is denoted by g. Using this notation and indexing individuals by i, Equation (1) gives the standard condition for indifference between the Medicare service and the VA service.

$$V_i - V_i e^{-g_i \tau} = p_i - c_i \tag{1}$$

This equation will hold for each service, as V, p, and c vary across services, producing an optimal choice of VA in some cases and Medicare in others. V will vary by service because the severity of illness or disability associated with each service could be different. The cost variables, p and c, will vary because eligibility determinations, insurance coverage, and courses of treatment will depend on the particular service requested. In addition, p will vary by Medicare plan because co-payments, coinsurance, and deductibles vary. Most Medicare plans also charge a premium, denoted by I, which we will assume is collected annually. Indexing services by k and Medicare plans by j, Equation (2) gives the sum of utility over a year, assuming a particular Medicare plan has been chosen.

$$
\begin{aligned}
&\sum_{k=1}^{K}\{M_{ijk}(V_{ik}-p_{ijk})+(1-M_{ijk})(V_{ik}e^{-g_i\tau}-c_{ik})\}-I_{ij} \\
&M_{ijk}=1 \text{ if } V_{ik}-V_{ik}e^{-g_i\tau}>p_{ijk}-c_{ik} \\
&M_{ijk}=0 \text{ if } V_{ik}-V_{ik}e^{-g_i\tau}<p_{ijk}-c_{ik}
\end{aligned} \tag{2}
$$

When the individual chooses a Medicare plan at the beginning of the year, she compares expected total utility from each plan and selects the one that provides the highest value. Simplifying notation, suppressing individual subscripts, and using the definition of covariance, Equation (3) expresses the individual's objective function in a more convenient form.

$$
\begin{aligned}
&\overline{M_j V_j}^{M}+\overline{VA_j V_j}^{VA}+\operatorname{cov}(M_{jk},V_{jk}^{M})+\operatorname{cov}(VA_{jk},V_{jk}^{VA})-\frac{I_j}{K} \\
&VA_{jk}=(1-M_{jk}) \\
&V_{jk}^{M}=(V_k-p_{jk}) \\
&V_{jk}^{VA}=(V_k e^{-g\tau}-c_k)
\end{aligned} \tag{3}
$$

Assuming for a moment that the choice of plan does not affect service-level VA-Medicare choices, then the VA covariance and the net utility from VA services are the same for all choices and the optimal choice will produce the maximum value of Equation (4), where m* denotes the latent marginal valuation of each plan and ε represents measurement error.

$$
m_j^{*}=\overline{MV_j}^{M}+\operatorname{cov}(M_k,V_{jk}^{M})-\frac{I_j}{K}+\varepsilon_j \tag{4}
$$

Assuming further that the net utility from Medicare services and the covariance terms are given by a linear function of variables denoted by X and that ε is independently and identically distributed according to a Type I extreme value distribution, Equation (5) gives the probability that a particular plan is selected, which can be estimated by a standard conditional logit.

$$\Pr(m_i = j) = \frac{e^{\beta' X_{ij}}}{\sum_{h=1}^{J} e^{\beta' X_{ih}}} \tag{5}$$

Variables in X include each plan's premium and the individual's health status and illness severity variables interacted with each plan's coverage variables as well as the covariance term. As shown in Equation (4), the value of coverage in each Medicare plan is mediated by the degree to which the individual relies on Medicare for her health services (the average value of the Medicare indicator, M), so each coverage-related element of X should be scaled by average Medicare reliance.

Under the assumption that Medicare reliance is independent of plan choice, Equation (5) can be estimated straightforwardly. Unfortunately, this is a very strong assumption, made only temporarily to simplify exposition. If we relax this assumption, the latent net valuation of each plan is given by Equation (3) and the two average reliance variables, $\overline{M}_j$ and $\overline{VA}_j$, are jointly determined with the choice of plan. Additional problems are that these variables cannot be observed for plan choices other than the one selected and the same is true for the covariance terms. We use an instrumental variables approach, which we will explain in detail in the next section, to address these issues.

Statistical Model

We begin to explain our statistical approach by re-writing Equation (3) as Equation (6), which gives latent net valuations without the assumption of independent Medicare reliance.

$$m_j^* = \overline{M}_j \overline{V}_j^{M} + \overline{VA}_j \overline{V}_j^{VA} + \mathrm{cov}(M_{jk}, V_{jk}^{M}) + \mathrm{cov}(VA_{jk}, V_{jk}^{VA}) - \frac{I_j}{K} + \varepsilon_j \tag{6}$$

In practice, Equation (6) simplifies to Equation (7) because the VA net valuations and Medicare and VA covariance terms for plans that are not chosen are unobservable to the researcher.

$$\begin{aligned} m_j^* &= \overline{M}_j \overline{V}_j^{M} - \frac{I_j}{K} + \tilde{\varepsilon}_j \\ \tilde{\varepsilon}_j &= \overline{VA}_j \overline{V}_j^{VA} + \mathrm{cov}(M_{jk}, V_{jk}^{M}) + \mathrm{cov}(VA_{jk}, V_{jk}^{VA}) + \varepsilon_j \end{aligned} \tag{7}$$

Equation (7) can be estimated by conditional logit as in Equation (5), except that $\overline{M}_j$ is endogenous. This endogeneity problem is due to the simultaneous determination of Medicare reliance and plan choice as well as to the fact that Medicare reliance is correlated with VA reliance in the new disturbance term.[1]

To instrument for Medicare reliance we need variables that affect the VA-Medicare choice at the service level but are constant across plans. Such variables would cancel out of the choice model given by Equation (5) and are therefore uncorrelated with the disturbance term. These variables include VA waiting times and distances to VA facilities as well as characteristics of other programs (like Medicaid) that might affect the

[1] Medicare reliance may also be correlated with the covariance terms, but these will be much smaller effects.

relative attractiveness of VA care. Additional instruments include local averages of Medicare plan characteristics and indicator variables for VA administrative regions.[2]

Given the nonlinearity of Equation (5), we use a two-stage residual inclusion technique to estimate the instrumental variables model (Terza et al., 2008). We estimate a model of Medicare reliance in the first stage, and then interact Medicare reliance and residuals from the first stage with Medicare coverage in the second stage choice model.

To estimate the first stage, we begin by recognizing that the distribution of Medicare reliance is truncated at both ends. Most veterans do not use the VA, so their Medicare reliance equals one. At the other extreme, some veterans rely exclusively on the VA, so their Medicare reliance equals zero. To account for the probability masses we observe at these endpoints (see Figure 1), we use a two-limit tobit model for the first stage model.

To estimate the second stage, accounting for the endogeneity of Medicare reliance, we estimate Equation (5), with the X vector including plan premium and interactions between Medicare reliance (1 – VA reliance) and plan characteristics including coverage, a Medigap indicator, and an HMO indicator. In addition, individual characteristics including age, sex, race, marital status, health status, and income are interacted with the Medigap and HMO indicators and all these variables are interacted with Medicare reliance. Next, any variable interacted with Medicare reliance is also interacted with the residual from the first stage. Finally year effects are included and treated as individual characteristics.

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[2] When using an instrumental variables approach it is standard to use overidentifying restrictions tests to determine whether the instruments are uncorrelated with the second stage disturbance term. Our instruments meet this condition by construction, so we do not conduct these tests.

A complication arises because the conditional logit model implies that, conditional on covariates, all choices are equally substitutable. This property, known as the independence of irrelevant alternatives (IIA) can be tested (Greene, 2003) and conditional logit models fail these tests when applied with similar data to the choice of Medicare plans (Atherly, Dowd and Feldman, 2004; Pizer, Frakt and Feldman, 2008, 2009). We follow Pizer, Frakt, and Feldman (2008, 2009) by selecting a nested logit model to address the rejection of IIA assumptions in the simple conditional logit.[3]

The nested logit model groups choices into "nests," allowing substitutability between choices within nests to differ from substitutability between nests. The IIA assumption still applies within nests, but it is more likely to hold if nests have been chosen that group similar choices together. Pizer, Frakt, and Feldman (2008, 2009) show that a three-nest structure (HMOs, Medigap plans, and traditional fee-for-service) passes within-nest IIA tests with MCBS data. This nesting structure is illustrated in Figure 2.

In the nested logit model choices within nests are modeled jointly with choices among nests. Equation (8) shows how these choices fit together in the model, with P_{ijk} denoting the probability of person i choosing plan j in nest k and $I_k = \ln(\sum_j e^{\beta X_{ijk}})$.

$$P_{ijk} = P_{ij|k} * P_k = \frac{e^{\beta X_{ijk}}}{\sum_j e^{\beta X_{ijk}}} * \frac{e^{\gamma I_k + \alpha Y_k}}{\sum_k e^{\gamma I_k + \alpha Y_k}} \tag{8}$$

X again denotes a set of plan characteristics and individual-plan interactions and Y represents individual-plan interactions that are constant within nest. The term denoted by I_k is known as the "inclusive value," and the estimated coefficient γ is known as the

[3] Even more flexible choice models are available, including the random coefficients logit. We chose the nested logit to be consistent with recent literature on Medicare choices and for tractability given the large number of variables and interactions in our model.

“inclusive value parameter.” This model is more flexible than the conditional logit model given by Equation (5) because the inclusive value parameters allow the coefficients of the X variables to shift from nest to nest while preserving their relative magnitudes within nests.[4] To account for the fact that the residuals from the first stage are estimated covariates in the second stage, we use bootstrapping with ??? replications to calculate standard errors for the choice model (Efron, 1979).

An additional complication arises because of timing. Most Medicare beneficiaries choose their health plan annually, so the frequency of observation for Equation (8) is annual. In contrast, choices between VA and Medicare for outpatient care occur more frequently, sometimes multiple times in a month, and most of the variation in VA waiting times is month-to-month, not year-to-year. As a result, we use a monthly model to measure the sensitivity of Medicare reliance to VA waiting times and then apply the results to a simulation of the effect of broad and persistent change in waiting times on utilization decisions and plan choices. We use two correlated zero-inflated negative binomial regressions, one to model monthly Medicare outpatient visits and one for VA visits occurring in the same month. We expect the disturbance terms in these regressions to be negatively correlated because Medicare and VA outpatient visits are substitutes. We use zero-inflated models because the distributions of outpatient visits of both types have large, seemingly discontinuous masses at zero (see Figure 3).

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[4] Note that if the inclusive value parameters are constrained to equal one, the nested logit is equivalent to a conditional logit.

Data and Sample

Our principal source of data is the 2001-2003 Medicare Current Beneficiary Survey (MCBS). MCBS is an ongoing panel survey of a nationally representative sample of Medicare beneficiaries. MCBS includes demographic variables, health insurance choices, health and functional status measure, diagnoses, utilization and expenditure data.

We are interested in veterans who have both VA and Medicare options. Therefore, our sample was all non-institutionalized individuals who reported they had served in the Armed Forces. We excluded veterans who had coverage from Medicaid or employer-sponsored retiree health plans. Models include lagged spending and health status information. Therefore, we excluded individuals with missing information from the previous year.

MCBS was supplemented with VA administrative, Medicare HMO and Medigap administrative data. Each person's resident ZIP code was taken from MCBS and the nearest VA facility was assigned.

The first stage equation predicts VA reliance (1-Medicare reliance) based on VA wait time, distance to the nearest VA facilities, non-VA Medicare options in the county, individual demographics and health status. The main VA wait time is the average number of days until the next available appointment for new patients. We assume new patients want to utilize VA services as soon as possible versus established patients who may choose follow-up appointments that are not the next available appointment. Validity checks comparing the wait time data for new patients to notes in the medical record confirmed this assumption (Mayo, YEAR?). Wait times are based on patient-provider interactions that cover all major medical sub-specialties (e.g. mental health, cardiology). In contrast, wait times for procedures (e.g. labs, x-rays) are often missing indicating that these procedures do not schedule appointments. For further information on the specification of the wait time variable refer to Prentice and Pizer (2007, 2008).

VA reliance was defined as the proportion of outpatient physician visits that occurred in the VA during the year. Unfortunately, MCBS measures of VA utilization are not accurate, so these figures must be removed and replaced with utilization counts based on VA administrative data. We followed methods in Gardner et al. (2008) to count Medicare and VA physician visits in a comparable way. A key instrument in this first-stage model was the state-level restrictiveness of Medicaid eligibility policy. Following Cutler and Gruber (1996) and Currie and Gruber (1996) we constructed a measure of Medicaid eligibility restrictiveness by applying detailed Medicaid policy rules obtained from the TRIM3 microsimulation model (Urban Institute, YEAR?) to a representative national microdata set. Additional details are provided in the Appendix.

The second stage equation predicts the likelihood of choosing between Medicare FFS, Medicare HMO and Medigap plans. Each MCBS respondent in our sample with Medigap or HMO coverage was linked to the plan in which they enrolled. MCBS does not provide sufficient information to match enrollees to non-standard Medigap plans in three waiver states (MA, MN and WI). Thus, observations from these states were excluded (Table 1 describes this and other sample derivation steps).

Each individual chooses between all available health plans in the county so plan-level benefits and cost-sharing data were merged with all plan choices an individual has. Medicare HMO benefits and cost-sharing were coded from the Medicare Personal Plan Finder (MPPF), publicly available on the CMS website. HMO premium, doctor visit cost-sharing, and drug cost-sharing variables were coded. Medigap premium data were obtained from a large insurer and reduced to two plan types, drug and non-drug, by an enrollment-weighted average of the premiums. Medigap premiums, doctor visit cost-sharing and drug cost sharing variables were coded. The benefits in our models are constant across non-drug Medigap plans. For the drug plans, we computed the enrollment-weighted average of the drug cap. Each individual also had the option of using Medicare FFS. Therefore, a FFS plan was added by constructing the relevant premium and cost-sharing variables. Finally, following the detailed methods described in Pizer, Frakt, and Feldman (2009), we constructed a variable called "coverage" that measures the amount of lagged individual drug and doctor visit spending that would have been covered by each available plan option.

Results

The effect of monthly variations in VA waiting times can be seen in the results from the correlated zero-inflated negative binomial regressions shown in Table 2. The left-hand three columns of Table 2 give results for the Medicare visits equation and the right-hand three columns give results for the VA visits equation. The first page of the table gives results for the count model and the second page gives the zero inflation model results. As predicted by theory, the monthly wait time (lagged by two months) had opposite effects on Medicare and VA visits in the count model. It was positively and significantly associated with Medicare visits and negatively but not significantly associated with VA visits. Furthermore, the interaction between wait time and an indicator variable for low-income or disabled priority status offset the effect of wait times alone for these veterans. In other words, unlike other veterans, these high-priority patients were not induced by increased waiting times to use more Medicare visits. Other noteworthy effects on the Medicare side were associated with the average value of coverage available from Medicare plans in the county (negative), the average Medicare plan premium in the county (positive), and the patient's total spending on prescription drugs and physician visits in the prior year (both positive). On the VA side, the restrictiveness of Medicaid eligibility policy in the state had a positive effect on VA visits and fair or poor health status had a borderline positive effect. The availability of health insurance through a spouse had a borderline negative effect.

Results from the zero inflation models show that disabled veterans were more likely to have zero Medicare visits and older or white veterans with hypertension or emphysema or high physician spending in the prior year were less likely to have zero visits. The estimate of the overdispersion parameter, alpha, supports the use of a negative binomial instead of a poisson regression model. Also, as predicted by theory, the residual from the Medicare count model was negatively associated with VA physician visits, suggesting that Medicare and VA visits are substitutes, but the effect was not statistically significant.

We used the estimates from this model to predict the effects of a one-standard deviation change in monthly waiting time on Medicare and VA physician visits for high-priority and low-priority veterans. A one-standard deviation increase would have raised the waiting time at the mean by about 13.6 days, from 45.1 to 58.7 days. As a result, our model predicts that VA reliance would have been reduced by six percent for high-priority veterans and ten percent for those with low-priority status.

The first stage of our plan choice model was to instrument for VA reliance using exogenous market characteristics. Results from a two-limit tobit model of VA reliance are shown in Table 3. The availability in the county of outpatient drug coverage from Medigap plans had a negative effect on VA reliance and the restrictiveness of state-level Medicaid eligibility policy had a positive effect. A joint test of the significance of these two instruments produced an F-statistic of 7.2, which is considered less than ideal but not dangerously low (Staiger and Stock, 1997). Other variables with significant effects included disability, fair or poor health status, hypertension, and arthritis (all increased VA reliance) and female and white (both decreased VA reliance). We used the results shown in Table 3 to calculate a predicted value of VA reliance for each person-year and then form a residual as the difference between actual and predicted values. We included this residual, interacted with all variables that interact with VA reliance, in the Medicare plan choice model.

Results from the Medicare plan choice instrumental variables nested logit model are shown in Table 4. The first four rows give results for the choice of plan, conditional on a choice of nest (HMO, Medigap, or FFS Medicare). Unsurprisingly, these results indicate that, holding other factors constant, veterans are less likely to choose a plan with high premiums and more likely to choose a plan with high coverage. The effect of VA reliance interacted with coverage was negative, indicating that those who rely more on the VA find the coverage offered by Medicare plans to be less attractive. All of these results are consistent with theory. The next two sets of results are for the choice of nest, first for the HMO nest and second for the Medigap nest. The only statistically significant effects were found in the Medigap nest variables, indicating that older, white, or married veterans were more likely to choose a Medigap plan, and those with fair or poor health status were less likely to do so. The estimate of the inclusive value parameter for the nested logit model (0.53) was significantly different from 1, demonstrating that substitutability between choices across nests was limited and supporting the use of the nested logit model.

We used the parameters of this choice model to simulate the effect of increased VA waiting times on the premiums paid to Medicare plans by veterans with high and low VA priority status. Because most of the variation in VA waiting times is month-to-month (annual averages eliminate about 90 percent of the variance), there is little empirical relationship between annual average wait times and VA reliance (see Table 3). For simulation purposes, we made the strong assumption that if waiting times were increased permanently, veterans would respond by reducing VA reliance in the same proportion as they do in response to monthly changes. Specifically, a one-standard deviation increase would induce a six percent reduction in VA reliance among high-priority veterans and a ten percent reduction among those with low-priority status. Making those changes to VA reliance in the annual choice model given by Table 4, we calculated the induced change in expected premium and coverage by priority status group. The results, shown in Table 5, indicate that changes in VA waiting times of this magnitude have little effect on Medicare plan choices for either priority status group. The total annual increase in out-of-pocket and premium spending, net of the value of improved coverage for physician visits and drugs, was $5 for high-priority veterans and $10 for those with low priority status.

Conclusion

We estimate the response by elderly veterans to variations in waiting times for outpatient physician visits available from the VA. We estimate changes in the numbers of Medicare and VA physician visits, changes in out-of-pocket costs, and changes in insurance premiums and coverage resulting from modified choices among Medicare insurance plans. Our results indicate that the financial impacts of VA waiting times on veterans are small, although these impacts are somewhat larger for low-priority veterans (those who are not disabled or low-income). This suggests that, although veterans adjust their utilization patterns to some degree, established clinical relationships probably prevent most veterans from making major changes in response to waiting times for outpatient care. This is an important contrast with waiting times for elective surgery, where established relationships are probably less influential. As a result, the cost of outpatient waiting times for patients is principally the benefit lost due to delayed care. The fact that high-priority veterans were less sensitive to variations in waiting times suggests that the VA's priority system is probably successful in reducing the burden of waiting times on these patients. A similar analysis that stratified our sample by chronic disease did not show any difference in sensitivity across groups (results not presented). This demonstrates that it is possible to distribute the burden of waiting times according to policy.

There are several significant limitations of this study. First, although a substantial fraction of Medicare beneficiaries are veterans (about one quarter), the veterans who consider using VA care are typically lower income, sicker, and more disabled than the average. This is partly due to the VA's priority system and partly attributable to established clinical relationships and perceptions of care quality. Consequently, our results may not be generalizable to the broader Medicare population. Second, we did not observe large, permanent variations in outpatient waiting times in our data. Our simulations, therefore, rely on the assumption that short run sensitivities to waiting times are the same as long run sensitivities. This assumption almost certainly leads to underestimates of long run responses. Another important limitation is that we do not observe the marginal benefit of the treatment that is postponed by waiting times. Lacking a measure of marginal benefit, we have to use proxies like health and disability status to assess the differential burden of waiting times. Finally, our sample sizes are somewhat limited. Data access restrictions imposed by the VA have prevented use of the VA crosswalk in more recent releases of MCBS. We expect these restrictions to be lifted soon.

Appendix

Construction of Medicaid Restrictiveness Variable

In a series of papers including Currie and Gruber (1996) and Cutler and Gruber (1996), Gruber and colleagues studied the effects of Medicaid eligibility expansions for women and children in the 1990s. To produce a summary measure of the relative expansiveness of Medicaid eligibility policy from state to state, they applied income thresholds from each state to a nationally representative sample from the Current Population Survey (CPS). The resulting figures measured the proportion of the national population that would have been eligible had the entire population lived in the corresponding state. In contrast to actual proportions of state populations enrolled, this measure reflects policy differences without the potentially confounding effects of state differences in income, employment, and medical costs. Unfortunately, because CPS does not collect data on medical spending or assets, Gruber and colleagues could not take medically needy programs into account.

Following this example, we constructed similar measures using income and asset thresholds for each state and a nationally representative sample from the Medical Expenditure Panel Survey (MEPS) from 1998. We chose MEPS instead of CPS because it includes detailed information on medical spending that enabled us to include thresholds for medically needy programs in our calculations. For expository convenience, we converted the results from a measure of expansiveness to a measure of restrictiveness by taking 1 minus the simulated proportion eligible.

We restricted our MEPS sample to those aged 25-61 or 65 and over, avoiding those aged 62-64 because they could have been receiving Social Security for disability or early retirement and it is important to distinguish between these potential categories of Medicaid eligibility. Our extract included variables on family income, marital status, education, disability status, employment, Medicare status, and spending on health services by source of financing. Employment was determined by receipt of wage income. Status as a parent was determined by linking observations by family identification code. SSI enrollment was determined from an SSI indicator or from receipt of SSI income.

Several steps were required to prepare the data for the simulation. First, we imputed detailed family income because MEPS only provides family income in bands defined as multiples of the federal poverty line. The imputation uses variables for income band, age, education, and employment status in a statistical model that adds a random component. A second statistical model is used to impute assets in two categories: financial assets and house and car. This statistical model was developed in other work using the Survey of Income and Program Participation and the Health and Retirement Survey (Frakt and Pizer, 2001). Next, another set of income and asset variables were computed for use in states with medically needy programs. These variables are lower, reflecting reductions in family income and financial assets attributed to medical expenses financed out-of-pocket or by Medicaid (we assume house and car assets are protected from Medicaid spend-down). We include Medicaid-financed care in the spend-down calculation under the assumption that this spending would have been financed out-of-pocket in the absence of Medicaid and because we do not want differences in actual Medicaid eligibility to affect our simulation.

Our simulation applies state policy variables to the constructed dataset and calculates simulated eligibility rates for each state. We begin by sorting observations into categories of potential eligibility: disabled, parents, and Medicare beneficiaries. Income and asset eligibility thresholds by eligibility category and state are available from the on-line documentation for the Urban Institute's TRIM3 microsimulation model (http://trim3.urban.org). Thresholds were obtained for all years from 1998 to 2002. For each category in each state and each year, our simulation determines a respondent's eligibility by comparing family income and assets to the appropriate threshold. If the state has a medically needy program that applies to the relevant eligibility category then the post-spend-down versions of income and asset variables are used. Respondents may qualify under multiple categories.

Appendix References

Currie J, Gruber J. Health Insurance Eligibility, Utilization of Medical Care, and Child Health. Quarterly Journal of Economics 1996; 111(2): 431-466.

Cutler DM, Gruber J. Does Public Insurance Crowd Out Private Insurance? Quarterly Journal of Economics 1996; 111(2): 391-430.

Frakt AB, Pizer SD. Tax Incentives for Long-Term Care Insurance: A Microsimulation Analysis, HCFE Policy Brief #2001-01. Available at www.hcfe.researh.va.gov

References

TO BE ADDED

Tables and Figures

Table 1. Derivation of Sample: Unique Persons		
	Number excluded	**Number remaining**
MCBS 2001-2003		22,960
Exclude if not veteran	17,427	5,533
Exclude if no lag year	1,736	3,797
Exclude if institutionalized or age 0-64	375	3,422
Exclude if in Medicaid or employer sponsored plan	1,612	1,810
Exclude if living in non-standard Medigap plan state (MA, WI, MN)	130	1,680
Inconsistent or missing data	169	1,511

Table 2. Monthly Physician Visits: Correlated Zero-inflated Negative Binomial						
	Medicare			**VA**		
Count	**Coeff**	**SE**	**z**	**Coeff**	**SE**	**z**
Residual				-0.0153	0.0118	-1.3
Wait2molag	**0.0039**	**0.0020**	**1.96**	-0.0056	0.0054	-1.04
Wait*priority	**-0.0032**	**0.0025**	**-1.26**	-0.0001	0.0053	-0.01
HMO in cnty	0.0264	0.0822	0.32	0.1546	0.1564	0.99
HMORx cty	0.0659	0.0853	0.77	0.0421	0.1631	0.26
MgapRx cty	0.0375	0.0990	0.38	-0.1410	0.2179	-0.65
Av coverage	-0.0005	0.0001	-4.19	-0.0001	0.0002	-0.49
Av premium	0.0004	0.0001	2.75	0.0001	0.0004	0.16
Mcaid restrix	-2.8595	3.4526	-0.83	18.6991	9.5427	1.96
VAMC Dist	-0.0018	0.0018	-1	-0.0043	0.0047	-0.92
MCDist^2	0.0000	0.0000	0.84	0.0000	0.0000	0.66
Clinic Dist	-0.0060	0.0035	-1.7	0.0060	0.0077	0.77
CDist^2	0.0000	0.0000	0.46	0.0001	0.0001	0.64
Income<24K	0.1093	0.1247	0.88	0.2365	0.1812	1.31
Disabled	0.1503	0.1156	1.3	0.5634	0.3334	1.69
Age	0.0104	0.0056	1.87	-0.0130	0.0144	-0.9
Female	-0.0064	0.1452	-0.04	-1.2631	0.7955	-1.59
White	0.2343	0.1108	2.11	-0.0054	0.7057	-0.01
Married	0.0508	0.0757	0.67	-0.0039	0.2791	-0.01
HS	-0.0379	0.0664	-0.57	-0.1703	0.4344	-0.39
College	0.0592	0.0874	0.68	0.0229	0.5697	0.04
HH size	-0.0646	0.0448	-1.44	0.0630	0.1772	0.36
L_f/p health	0.0414	0.0709	0.58	0.3028	0.1622	1.87
L_eversmok	-0.0122	0.0734	-0.17	-0.1758	0.2339	-0.75
L_hypertens	-0.0559	0.0548	-1.02	0.3369	0.3229	1.04
L_heartprob	0.1252	0.0548	2.29	-0.0534	0.1340	-0.4
L_stroke	0.1575	0.0880	1.79	0.5493	0.6531	0.84
L_anycancer	0.0730	0.0544	1.34	0.2427	0.1714	1.42
L_diabetes	0.0534	0.0642	0.83	0.0707	0.2625	0.27
L_arthritis	0.1753	0.0542	3.23	0.3282	0.3126	1.05
L_alzheim	-0.1133	0.2740	-0.41	0.2017	0.4939	0.41
L_emphys	-0.0228	0.0775	-0.29	0.0171	0.2370	0.07
L_psych	-0.0831	0.0922	-0.9	0.4411	0.5583	0.79
L_anyadl	-0.2517	0.1415	-1.78	-0.2611	0.3444	-0.76
Spousecov	0.1010	0.1391	0.73	-0.8882	0.4941	-1.8
L_rxspend	0.0002	0.0000	6.51	-0.0001	0.0002	-0.41
L_docspend	0.0006	0.0001	4.76	0.0000	0.0002	0.15
Constant	1.1768	3.3306	0.35	-19.2275	9.3400	-2.0600

Table 2 Continued. Monthly Physician Visits: Zero Inflation						
	Medicare			VA		
Zero inflation	**Coeff**	**SE**	**z**	**Coeff**	**SE**	**z**
Income<24K	0.0452	0.1832	0.25	-0.2721	0.6847	-0.4
Disabled	1.2660	0.2735	4.63	-2.4781	7.8593	-0.32
Age	-0.0511	0.0181	-2.82	-0.0530	0.0806	-0.66
Female	-0.0856	0.4580	-0.19	1.4087	2.5898	0.54
White	-0.7781	0.2498	-3.11	1.1920	2.5086	0.48
Married	-0.4139	0.2269	-1.82	0.2578	1.3003	0.2
HS	-0.2149	0.1961	-1.1	-0.1695	1.8815	-0.09
College	-0.1564	0.2436	-0.64	0.8782	0.5709	1.54
HH size	-0.1316	0.1416	-0.93	0.1467	0.4102	0.36
L_f/p health	0.3824	0.2495	1.53	0.0956	0.5867	0.16
L_eversmok	0.1024	0.2095	0.49	0.3336	0.7375	0.45
L_hypertens	-0.3330	0.1693	-1.97	-0.1991	1.0932	-0.18
L_heartprob	0.2068	0.1884	1.1	-0.4769	0.6472	-0.74
L_stroke	0.3988	0.2889	1.38	0.4923	3.7300	0.13
L_anycancer	0.2877	0.1770	1.63	0.3068	0.7198	0.43
L_diabetes	-0.2028	0.2707	-0.75	0.1019	1.4940	0.07
L_arthritis	0.0515	0.1668	0.31	0.1468	1.2514	0.12
L_alzheim	0.5686	0.8218	0.69	0.3320	2.6773	0.12
L_emphys	-0.5175	0.2737	-1.89	-0.7603	0.7237	-1.05
L_psych	-0.3274	0.3927	-0.83	-0.4501	3.2918	-0.14
L_anyadl	0.6334	0.6218	1.02	-0.6093	2.8505	-0.21
Spousecov	-1.0747	0.7122	-1.51	-16.0555	2.9503	-5.44
L_rxspend	0.0000	0.0001	0.14	-0.0023	0.0017	-1.31
L_docspend	-0.0039	0.0006	-6.51	0.0000	0.0003	-0.12
Constant	6.1800	1.4700	4.19	4.5054	6.8707	0.66
alpha	1.6014	0.0459	34.89	1.9951	0.8693	2.29
Person-months	23,917					
Monthly and network dummies omitted from count model. Monthly dummies omitted from zero/nonzero model. L_ indicates variable coded from prior year’s data. Robust standard errors clustered on individuals.						

Table 3. Annual VA Reliance: Two-limit Tobit

	Coeff	SE	t	P>|t|
HMO in county	0.1097	0.0726	1.51	0.131
HMORx in cty	-0.0225	0.0635	-0.35	0.723
MgapRx in cty	-0.1706	0.0800	-2.13	0.033
Avg coverage	0.0000	0.0001	0.21	0.836
Avg premium	0.0001	0.0001	0.77	0.44
Mcaid restrix	9.0010	2.8755	3.13	0.002
VAMC dist	0.0006	0.0017	0.35	0.728
MCDist^2	0.0000	0.0000	0.01	0.993
Clinic distance	0.0024	0.0033	0.74	0.46
CDist^2	0.0000	0.0000	0.22	0.824
Income<24K	0.0980	0.1022	0.96	0.338
Disabled	0.5400	0.0924	5.85	0
Annual wait	-0.0013	0.0028	-0.45	0.656
Wait*Priority	0.0002	0.0022	0.1	0.919
Age	-0.0056	0.0041	-1.36	0.173
Female	-0.4011	0.1908	-2.1	0.036
White	-0.2165	0.0893	-2.42	0.015
Married	-0.0114	0.0589	-0.19	0.847
HS	-0.0628	0.0517	-1.21	0.225
College	-0.0959	0.0726	-1.32	0.186
HH size	0.0067	0.0316	0.21	0.831
L_f/p health	0.2039	0.0515	3.96	0
L_eversmok	-0.0716	0.0584	-1.23	0.22
L_hypertens	0.1528	0.0454	3.36	0.001
L_heartprob	0.0171	0.0471	0.36	0.716
L_stroke	0.1065	0.0666	1.6	0.11
L_anycancer	-0.0259	0.0459	-0.56	0.573
L_diabetes	0.0639	0.0526	1.22	0.224
L_arthritis	0.1148	0.0437	2.63	0.009
L_alzheim	0.1969	0.1367	1.44	0.15
L_emphys	0.0566	0.0629	0.9	0.368
L_psych	0.1312	0.0760	1.73	0.085
L_anyadl	0.0215	0.1010	0.21	0.832
Spousecov	-0.1178	0.1202	-0.98	0.327
L_rxspend	0.0000	0.0000	0.49	0.626
L_docspend	0.0000	0.0001	-0.58	0.563
year02	-0.0066	0.0394	-0.17	0.868
year03	0.0268	0.0476	0.56	0.574
Constant	-8.6321	2.7687	-3.12	0.002
sigma	0.6340	0.0282	Person-years	2,004

Network dummies omitted.
Robust standard errors clustered on individuals

Table 4. Medicare Plan Choice: Instrumental Variables Nested Logit				
	Coeff	**SE**	**z**	**P>|z|**
Choice of plan				
Premium	-0.0006	0.0001	-10.35	0
Coverage	0.0013	0.0001	11.59	0
Cov*VArely	-0.0029	0.0004	-7.17	0
Cov*Resid	0.0028	0.0003	9.31	0
Choice of nest				
HMO				
VA reliance	-16.6991	9.7885	-1.71	0.088
Residual	13.3734	10.2276	1.31	0.191
Age	-0.0115	0.0226	-0.51	0.612
Female	1.0975	0.8141	1.35	0.178
White	0.5999	0.4900	1.22	0.221
Married	0.1485	0.2816	0.53	0.598
f/p health	-0.2655	0.3400	-0.78	0.435
Income in K	-0.0002	0.0035	-0.05	0.961
year02	0.2277	0.2873	0.79	0.428
year03	0.2423	0.3125	0.78	0.438
Disabled	0.1653	0.7216	0.23	0.819
Age*VArely	0.2101	0.1241	1.69	0.09
Age*Resid	-0.2028	0.1284	-1.58	0.114
Female*VArely	-6.9701	10.2411	-0.68	0.496
Female*Resid	4.6445	10.0350	0.46	0.643
White*VArely	-0.1369	2.0371	-0.07	0.946
White*Resid	-0.0257	2.1789	-0.01	0.991
Married*VArely	1.9650	1.5737	1.25	0.212
Married*Resid	-2.8294	1.6554	-1.71	0.087
f/phealth*VArely	-0.1037	1.4700	-0.07	0.944
f/phealth*Resid	-0.1137	1.6225	-0.07	0.944
Income*VArely	0.0027	0.0366	0.07	0.941
Income*Resid	0.0708	0.0384	1.84	0.065
year02*VArely	-1.3166	1.4745	-0.89	0.372
year02*Resid	1.6052	1.6286	0.99	0.324
year03*VArely	-3.0124	1.7636	-1.71	0.088
year03*Resid	2.4088	1.8276	1.32	0.187
Disabled*VArely	-1.6820	2.0402	-0.82	0.41
Disabled*Resid	2.8454	2.1668	1.31	0.189
Constant	-0.3440	1.8148	-0.19	0.85

Table 4 Continued. Medicare Plan Choice: IV Nested Logit				
	Coeff	**SE**	**z**	**P>|z|**
Choice of nest				
Medigap				
VA reliance	-8.4565	7.6736	-1.1	0.27
Residual	13.7669	8.0377	1.71	0.087
Age	0.0667	0.0171	3.89	0
Female	1.1062	0.7567	1.46	0.144
White	1.1470	0.4491	2.55	0.011
Married	0.6053	0.2234	2.71	0.007
f/p health	-0.5134	0.2589	-1.98	0.047
Income in K	0.0008	0.0023	0.34	0.731
year02	-0.1806	0.2282	-0.79	0.429
year03	-0.3635	0.2353	-1.54	0.122
Disabled	-0.0151	0.5583	-0.03	0.978
Age*VArely	0.0771	0.0952	0.81	0.418
Age*Resid	-0.2048	0.1000	-2.05	0.041
Female*VArely	-14.4106	11.0617	-1.3	0.193
Female*Resid	9.4038	10.3286	0.91	0.363
White*VArely	1.1239	2.0631	0.54	0.586
White*Resid	0.0144	1.9984	0.01	0.994
Married*VArely	0.3397	1.2076	0.28	0.778
Married*Resid	0.2284	1.2345	0.18	0.853
f/phealth*VArely	-1.1437	1.1584	-0.99	0.323
f/phealth*Resid	0.2500	1.2262	0.2	0.838
Income*VArely	0.0205	0.0230	0.89	0.373
Income*Resid	0.0046	0.0168	0.27	0.784
year02*VArely	0.2398	1.2554	0.19	0.848
year02*Resid	0.0023	1.3328	0	0.999
year03*VArely	0.3510	1.2894	0.27	0.785
year03*Resid	-0.4258	1.3672	-0.31	0.755
Disabled*VArely	-1.5199	1.6272	-0.93	0.35
Disabled*Resid	2.0440	1.6937	1.21	0.228
Constant	-5.0548	1.4089	-3.59	0
Incl. val. Param	0.5292	0.0693	IIA P > ChiSq	0
Person-plan-yrs	10,253	Person-years	2,004	

Table 5. Simulation Results: One SD Increase in VA Outpatient Waiting Time						
	VA Priority = High			**VA Priority = Low**		
	Baseline	**Sim**	**Change**	**Baseline**	**Sim**	**Change**
Monthly Mcare visits	1.20	1.21	0.01	1.44	1.51	0.07
Annual visit + Rx OOP cost	$206	$208	$2	$247	$259	$12
Annual Mcare plan premium	$974	$980	$6	$1,150	$1,155	$5
Annual Mcare plan coverage	$2,392	$2,395	$3	$2,635	$2,642	$7
Premium + OOP - coverage			$5			$10

Figure 1. Distribution of Annual VA Reliance

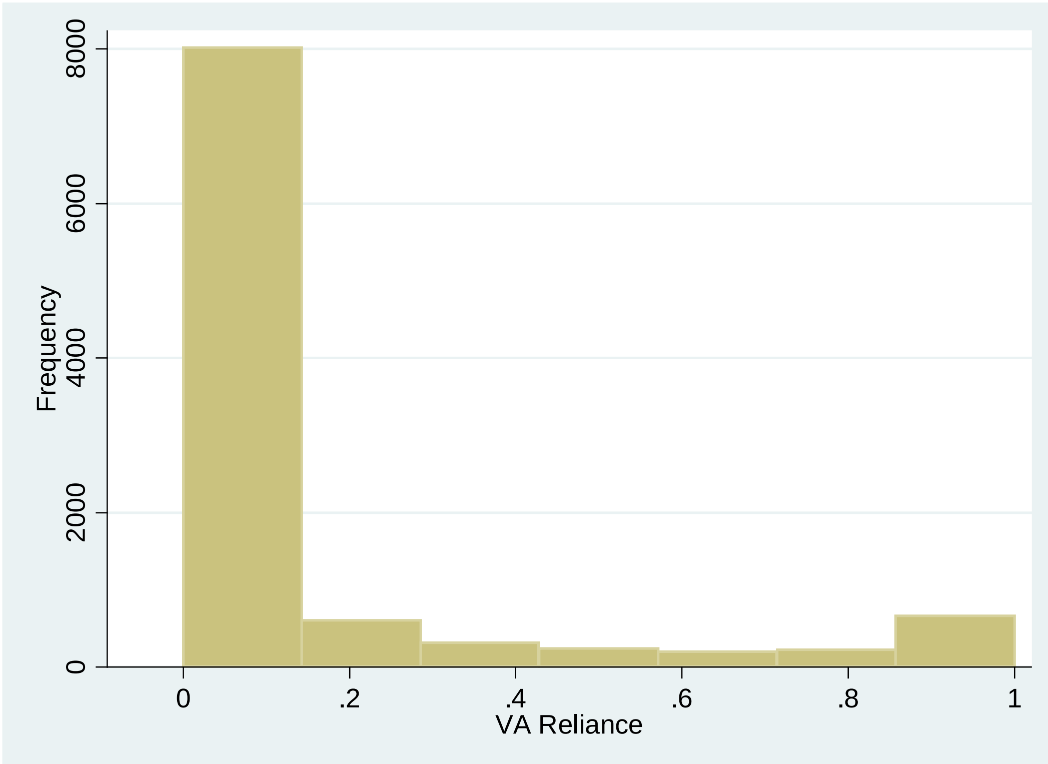

Figure 2. Medicare Plan Choice Nesting Structure

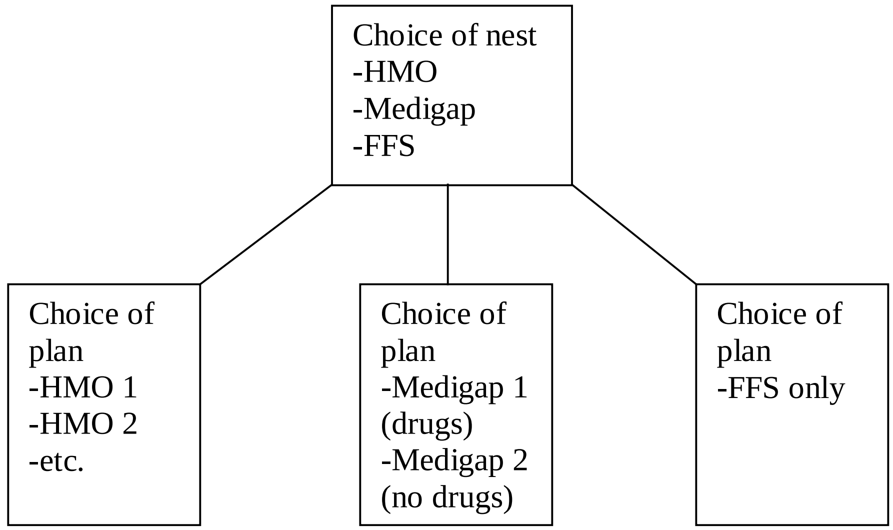

Figure 3a. Distributions of Monthly Physician Visits

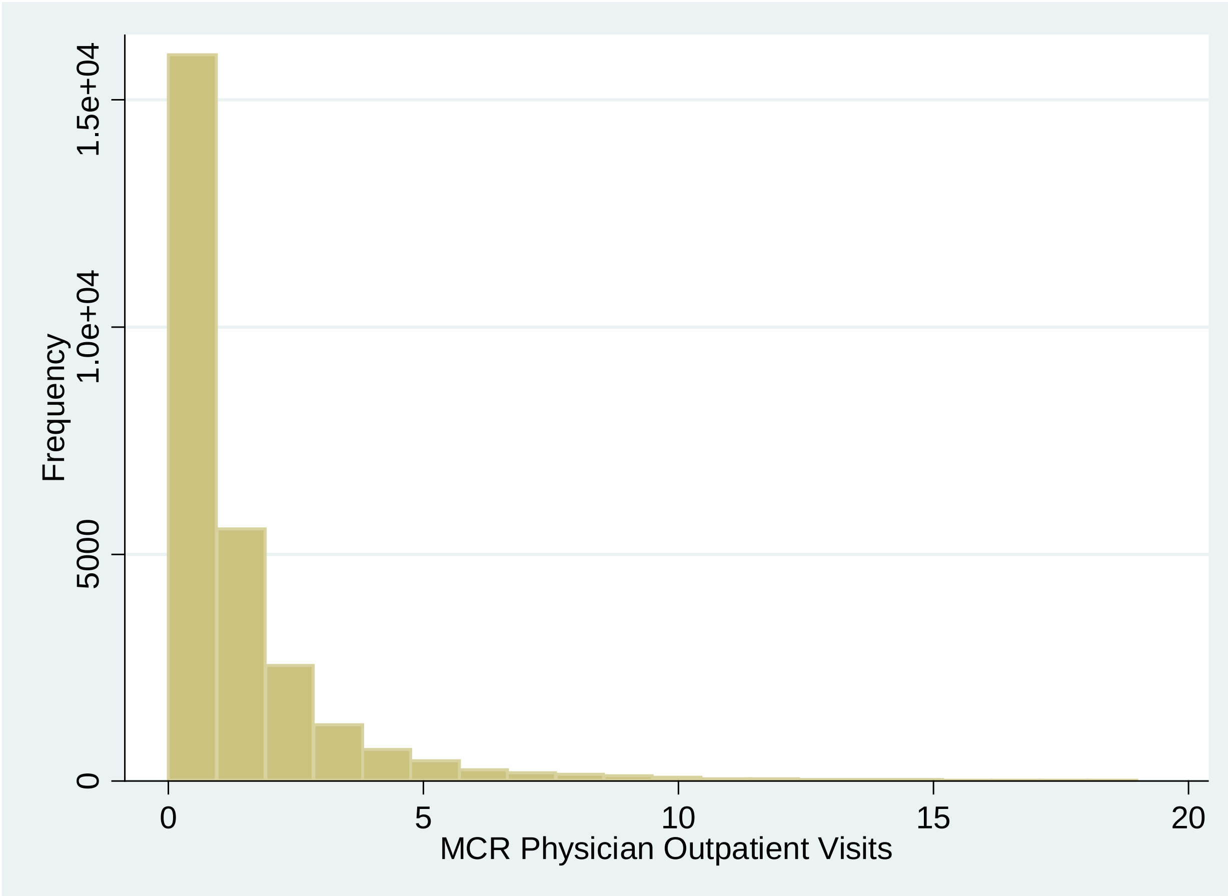

Figure 3b. Distributions of Monthly Physician Visits