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Abstract

This study develops a discrete multiple state duration model that allows for duration dependence, unmeasured heterogeneity, partial observability of the state and endogenous time-varying treatment. Our econometric strategy has numerous potential empirical applications. We apply our duration model to the progression of diabetic neuropathy, a complication of diabetes with four levels of progression, which if left untreated may lead to amputation. Our results show that the longer a person has diabetes without having being diagnosed (and treated) increases the probabilities of transitioning to a worse stage, death or amputation.

Keywords: Multiple state duration model, endogenous treatment, discrete factors.

JEL classification: C41; C14; C51; I12

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1 Introduction

For many outcomes, the timing and length of the treatment or intervention cannot be ignored. An educational program such as Head Start, for example may have a different effect if applied to young children, than if in somewhat altered form, it is applied to teenagers (Garces et al., 2002 and Cunha and Heckman, 2007). Or the effects of a change in unemployment benefits will have a different effect if the individual is unemployed for one week rather than four months and will depend on the phase of business cycle (Lechner and Wunsch, 2009). Similarly, in a medical context, treatment for a chronic condition, such as chemotherapy for cancer, has a different impact if applied after the cancer has diffused rather than when the cancer is limited to a single organ (Llobera et al., 2000). Further, there may be duration dependence in which the probability of an individual transitioning out of a particular state depends on the time spent in that state, e.g., the probability of an individual accepting a job offer depends on how long s/he has been unemployed. Duration models have long been used in these situations (Kiefer 1988, Lancaster 1990 and van den Berg 2001).

There is a growing econometric literature on endogenous treatment effects in duration models: Robins (1989, 1997), Gill and Robins (2001), Abbring and van den Berg (2003), Mroz and Savage (2006), Heckman and Navarro (2007), Abbring and Heckman (2008), and Liu et al (2009) among others. This literature has established conditions under which the treatment effects are identified and how they can be estimated using minimal assumptions. For more complicated models such as multiple duration models, accounting for endogeneity of an explanatory variable remains a daunting computational challenge.[1] This paper contributes to this literature by developing a discrete multiple state duration model that allows for duration dependence, unmeasured heterogeneity, partial

[1] See Richardson and van den Berg (2008) for a recent study of vocational Swedish labor market training on unemployment spells.

observability of states and endogenous time-varying treatment.

We apply our dynamic multi-stage discrete duration model to study whether early detection of diabetes mellitus is effective in delaying progression to diabetic neuropathy, which are complications of the lower extremities (legs and feet). If untreated, diabetic neuropathy may lead to amputation. We also study whether early diagnosis of more advanced stages slows disease progression. Treatment is defined in terms of timing of visits to doctors. Our model allows for unmeasured heterogeneity using discrete factor models (Heckman and Singer, 1984), duration dependence, partial observation on one's current disease state, and right-censoring. For each time period, we model: the probability of the disease progressing to a more severe stage; the probability of receiving treatment (visits); and the probability of experiencing various health shocks. Following Mroz (1999), we control for endogeneity of treatment by allowing unobserved discrete factors, aspects of health unobserved by the researcher, to affect probabilities of disease progression, receipt of treatment, and occurrence of health shocks. This strategy has been used by Glewwe and Jacoby (2004), Bhattacharya (2005), Mroz and Savage (2006), and Liu et al. (2010) among others. However, the likelihood function estimated here is more computationally complex than in previous studies since we simultaneously account for multiple disease stages, partial observability of disease progression, endogeneity of treatments, and health outcomes.

Our duration model is well suited for analysis of effects of treatment (early diagnosis in our study) on progression of diabetes mellitus; our method has several advantages over previous studies that attempt to control for the endogeneity of treatment using standard models in which the dependent variable is continuous and it is controlled by a single index (see e.g., Picone et al., 2004). First, disease progression often occurs over a long time period. Even if a partic-

ular treatment is productive, it may only affect a temporally distant outcome, which is also subject to future treatment. Our duration model allows us to make more precise inferences about these distant outcomes than is possible using a standard specification in which outcomes are measured at fixed intervals with no allowance for possible effects of future treatment. Second, we can directly model the effect of early diagnosis on the disease progression and outcomes. A timely diagnosis and treatment is usually the main reason behind many doctor visits and screening tests like mammography. Standard methods infer benefits of early diagnosis of cancer, for example, by analyzing effects of shorter screening intervals on the number of malignancies detected and the time individuals live with cancer. However, this approach suffers from lead bias. Just because people live longer with cancer does not necessarily imply that treatment is effective (Cole and Morrison, 1980). By modeling the time with the undiagnosed disease directly, our approach controls for the lead bias problem. Third, our approach allows for right or left censoring as well as partial observability of the disease stage. Fourth, we allow marginal productivity of treatment to be time varying and to depend on the disease stage. Fifth, our approach allows analysis of duration dependence separately from earlier diagnosis.

We find that earlier diagnosis of diabetes, and presumably treatment that follows diagnosis, delays onset of lower extremity complications including amputation. At the same time there is positive duration dependence, regardless of whether diabetes was diagnosed or not; the probability of contracting neuropathy and all subsequent stages including mortality and amputation increases with the length of time since the onset of diabetes and other subsequent stages. We also find that visits to a podiatrist are more effective in slowing onset of complications of diabetes neuropathy than are visits to other health professionals.

The rest of the paper is organized as follows: Section II provides background information on diabetes. Section III describes the econometric model and Section IV the data. Section V presents our empirical specification, including the method for accounting for endogeneity of treatments, which is followed by results in Section VI. Finally, Section VII presents conclusions and implications.

2 Background

Diabetes mellitus is a complex disease, potentially affecting several organ systems, including the eyes, the cardiovascular system, and the kidneys as well as legs and feet; it reduces life expectancy. Because some individuals with diabetes experience loss of sensation in their legs and feet, they are more subject to injury. Diabetic complications of the lower extremities are classified as diabetic neuropathy. Individuals can reduce disease progression by keeping a healthy diet, exercising, regularly monitoring their blood glucose levels and blood pressure, obtaining medical care and following their physicians' recommendations (e.g., taking drugs as prescribe). If diabetic neuropathy is untreated, it may lead to an amputation of a toe, a foot, part of a leg or even death.

Medical care of persons with diabetes involves diagnosis of disease progression and complications, direct provision of treatments, referrals to specialists for other treatments of the underlying disease, prescribing drugs, and instructing patients on self-care.

Important randomized controlled trials (RCT) have documented the productivity of various regimens, such as blood glucose control, in slowing the progression of the disease (Montori et al., 2006). However, RCTs tend to have short follow-up periods, and patients enrolled in RCTs are subject to being on strict medical protocols, which neither health professionals nor patients may follow when not subject to those protocols. Monitoring longer term effects of

treatment and how patients and doctors behave in the community when they are not subject to RCT protocols requires analysis with observational data.

Table 1 presents a description of the stages of diabetic neuropathy and the associated ICD-9 codes used to identified them. We classify diabetes mellitus and diabetic neuropathy into 5 mutually exclusive progressive stages: (1) healthy (no DM); (2) diabetes mellitus only (DM); (3) diabetic neuropathy stage 0 (DNU_0); (4) diabetic neuropathy stage 1 (DNU_1), and (5) diabetic neuropathy stage 2 (DNU_2). Once an individual turns 65, stages were assigned on a quarter by quarter basis. Individuals were classified as continuing to be healthy (no DM) if, over the course of three months, they have had one or more visits to a doctor who could have made a diagnosis of diabetes, but a positive diagnosis did not occur. An individual was classified as having diabetes only (DM), if the individual had at least one Medicare claim that included an ICD-9 DM diagnosis code in that quarter or earlier, but none included a diabetes neuropathy diagnosis code. Once an individual is diagnosed with DM s/he was categorized to have DM or worse for the remainder of his/her life. A similar process was used to follow an individual's progression through the higher stages of the disease. Also, if an individual was diagnosed with a later stage of diabetes like DNU_1, we categorize him/her with that stage of diabetes and as having transited through all of the less severe stages. This approach allows us to model individuals who were not observed in a less severe stage in the course of their progression, perhaps due to long intervals between doctor visits, non-compliance with the treatment regiment or other reasons.

Physician visits may involve establishing a diagnosis, making referrals to other health professionals, provision of patient education and advice, and provision of specific therapies. The marginal product of a particular treatment modality is likely to differ by disease stage. For example, the marginal prod-

uct of therapeutic shoes, which provide protection from bumping into objects is plausibly much higher at Stage 3 than at Stage 5 when much damage to lower extremities has already occurred. Our dynamic approach allows for the marginal product of visits to differ by disease stage.

Our classification of disease stages is imperfect. Patients may report signs and symptoms of DM to physicians which are not recorded as ICD-9 and CPT codes on claims. Also, ICD-9 and CPT codes do not typically convey clinical findings which may in turn guide clinical decisions. This is an additional source of omitted heterogeneity but it is not clear whether it will bias the estimates. However, it will certainly lead to higher standard errors. We assume an individual specific heterogeneity whose impact on outcomes, visits, and transitions varies with the disease stage.

3 Modelling a Chronic Disease

We develop a discrete multi-stage hazard model to study the effect of visits to health professionals on outcomes associated with a chronic disease. For each period, we jointly model disease progression, the probability of a doctor visit, and the probability of a health shock. Health shocks take the form of either amputation or death.

Without loss of generality, we assume an individual is in one of 5 possible states: *no* DM, DM, DNU_0, DNU_1, and DNU_2 at each point in time. Once a person enters a more severe disease stage, it is impossible to recover and return to a less severe stage. The physical damage to diabetic progression is cumulative. To simplify notation, we suppress the subscript i. We select the sample conditional on the individual being alive at age 65. The first 3 periods are included to model the probability of entering DM and/or DNU_0 before

the person became Medicare eligible at age 65.[2] We use 3 periods to model the probability of being healthy by 65, entering DM only by age 65, and progressing to DNU_0 or a worse diabetic neuropathy stage by age 65. Right censoring can occur due to mortality (modeled as an outcome), leaving the sample, enrolling in an HMO, or any other reason at any time. Period 4 starts when the person becomes 65.

Let T be the last period that the individual is in our sample. The hazard function for the progression to DM at time $t > 3$ is

$$h_t^{DM}\left(DM_t = 1 | X_t^{DM}, e_k, DM_{t-1} = 0\right) = \Lambda\left(X_t^{DM}\beta_{DM} + \rho_{DM}\left(e_k\right)\right) \qquad (1)$$

where $\Lambda\left(z\right) = e^z / \left(1 + e^z\right)$, X_t^{DM} is a vector of potentially time varying explanatory variables and e_k is the unmeasured heterogeneity assumed to be discrete with K heterogeneity points.[3] Unmeasured heterogeneity affects the hazard of progression to a higher stage, probabilities of having a visit, and health shocks. For $t \leq 3$, the hazard function has a form that is identical to (1), but we allow for different explanatory variables and coefficients on these variables.

Let t_{DM} be the time at which the individual acquires DM; t_0 measures the time at which the individual progress to DNU_0. t_1 and t_2 are the corresponding times for entering DNU_1 and DNU_2, respectively. Once the individual acquires DM s/he is at risk for progressing to DNU_0 and subsequent stages of neuropathy. The hazard function for the progression to DNU_0 at time $t \geq t_{DM}$ is

$$\begin{aligned} &h_t^{DNU_0}\left(DNU_{0t} = 1 | t^{DM}, X_t^{DNU_0}, e_k, DNU_{0t-1} = 0\right) = \\ &\Lambda\left(X_t^{DNU_0}\beta_{DNU_0} + \delta_0\left(t^{DM}\right) + \rho_{DNU_0}\left(e_k\right)\right) \end{aligned} \qquad (2)$$

[2] We use three pre-age 65 time periods to allow for location specific and possibly time varying factors to affect the diseases progression.

[3] See Mroz (1999) and the appendix.

where $t^{DM} = t - t_{DM}$ is the duration of time since the DM onset and $\delta_0(.)$ is a quadratic function. Similarly, the hazard rates for DNU_j at time $t \geq t_{j-1}$ $(j = 1, 2)$ is given by

$$\begin{aligned} & h_t^{DNU_j}\left(DNU_{jt} = 1 | t^{DM}, ..., t^{DNU_j}, X_t^{DNU_j}, e_k, DNU_{jt-1} = 0\right) = \\ & \Lambda(X_t^{DNU_j}\beta_{DNU_j} + \delta_{DM,j}\left(t^{DM}\right) + \\ & \sum_{l=1}^{j} \delta_{l-1,l}\left(t^{DNU_{l-1}}\right) + \rho_{DNU_j}(e_k)) \end{aligned} \tag{3}$$

where $t^{DNUj} = t - t_j$ is time with DNU_j and $\delta_{DM,j}(.)$ is a quadratic function. These hazard functions depend on how long the individual has spent in each of the previous stages (t^{DM}, $t^{DNU_{j-1}}$) and allow for different sets of regressors depending on the disease stage.

In each period, the individual decides whether or not to visit a health professional. During that visit, the doctor determines a diagnosis based on the person's diabetes state at that time $(noDM, DM, DNU_0, DNU_1, DNU_2)$ and may perform a procedure to prevent or forestall disease progression. The probability of having a visit in period t depends on the disease stage. For a healthy individual $(noDM)$, this probability is

$$\Pr(DV_t = 1 | Z_t, e_k) = \Lambda(Z_t\beta_{DV} + \rho_{DV}(e_k)) \text{ if } t < t_{DM}. \tag{4}$$

For an individual at stage j $(j = DM, DNU_0, DNU_1, DNU_2)$, the probability of a visit during the period is

$$\begin{aligned} & \Pr\left(DV_t = 1 | t^{DM}, ..., t^{DNU_j}, Z_t, e_k\right) \\ = \; & \Lambda\left(Z_t\beta_{DV} + \sum_{l=1}^{j}\left(\alpha_{0,l} + \alpha_{1,l}t^l\right) + \rho_{DV}(e_k)\right). \end{aligned} \tag{5}$$

Among the regressors are variables that do not directly affect disease progression, e.g., distance to the health professionals. The variables help identify the effect of visits on disease progression.

Finally, let d be an observable health shock. We model both amputation and death. As the disease progresses, the probability of a health shock occurring is likely to change. For individuals without DM, the probability of a shock is

$$\Pr\left(d_t = 1 | W_t, e_k\right) = \Lambda\left(W_t\beta_d + \rho_d\left(e_k\right)\right) \text{ if } t < t_{DM}. \tag{6}$$

For an individual at stage j ($j = DM, DNU_0, DNU_1, DNU_2$), the probability of a health shock during each time period is

$$\begin{aligned} &\Pr\left(d_t = 1 | t^{DM}, ..., t^{DNU_j}, W_t, e_k\right) = \\ &\Lambda\left(W_t\beta_d + \sum_{l=1}^{j}\left(\gamma_{0,l} + \gamma_{1,l}t^l\right) + \rho_d\left(e_k\right)\right) \end{aligned} \tag{7}$$

We assume all events are independent after accounting for the unobservable heterogeneity e_k. Based on the hazards and probabilities of equations 1-7, the likelihood function for an individual with any possible transition combination conditional on the unmeasured heterogeneity e_k and the matrix of all possible

explanatory variables $\mathbf{M} = \left(\overrightarrow{\mathbf{X}}^{DM}, \overrightarrow{\mathbf{X}}^{DNU_0}, ..., \overrightarrow{\mathbf{X}}^{DNU_2}, \overrightarrow{\mathbf{Z}}, \overrightarrow{\mathbf{W}}\right)$[4] is

$$
\begin{aligned}
&L\left(t_{DM}, t_0, t_1, t_2, T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right) = L_{nDM}\left(T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right)^{1(t_{DM} \geq T)} \\
&\times L_{DM}\left(t_{DM}, T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right)^{1(t_0 \geq T > t_{DM})} \\
&\times L_{DNU_0}\left(t_{DM}, t_0, T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right)^{1(t_1 \geq T > t_0)} \\
&\times L_{DNU_1}\left(t_{DM}, t_0, t_1, T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right)^{1(t_2 \geq T > t_1)} \\
&\times L_{DNU_2}\left(t_{DM}, t_0, t_1, t_2, T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right)^{1(T > t_2)} \qquad (8)
\end{aligned}
$$

$L_{nDM}\left(T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right)^{1(t_{DM} \geq T)}$ is the likelihood function for an individual who did not progress to DM by period T with a sequence of visits $\overrightarrow{DV} = (DV_1, ..., DV_T)$ and health shocks $\overrightarrow{d} = (d_1, ..., d_T)$. $L_{DM}(.)$ is the likelihood function for an individual who contracted DM at t_{DM}, but did not progressed to DNU_0 by terminal period T. We define $L_{DNU_0}(.)$, $L_{DNU_1}(.)$, and $L_{DNU_2}(.)$, similarly. See Appendix A for more details on the construction of the likelihood function.

Without the unrealistic assumption that individuals continuously monitor, observe, and report their actual diabetes stage at each point in time, it is crucial to incorporate the partial observability of the one's diabetic stages into the construction of the likelihood function. We do this by integrating over the possible time periods during which an individual is known to have progressed to a more serious disease stage. This is similar to the strategy used by Mroz and Weir(1990) to address the partial observability of lactational amenorrhea in their life-cycle model of fertility control. As discussed above, the information to construct these bracketed time periods comes from the timing of doctor visits and the Medicare claims data. Using information on the date of the last doctor

[4] $\overrightarrow{\mathbf{X}}^{DM}$ is the sequence of all possible values of X^{DM} $\left(X_1^{DM}, ..., X_T^{DM}\right)$. We also define $\overrightarrow{\mathbf{X}}^{DNU_0}$, $\overrightarrow{\mathbf{X}}^{DNU_1}$, $\overrightarrow{\mathbf{X}}^{DNU_2}$, $\overrightarrow{\mathbf{Z}}$, and $\overrightarrow{\mathbf{W}}$ the same way.

visit without the condition having been present and the first doctor visit with the condition, we know the earliest ($t_{\min,j}$) and latest ($t_{\max,j}$) time periods in which t_{DM}, t_0, t_1, and t_2 may have occurred

$$t_{\min,j} \leq t_j \leq t_{\max,j}$$

for $j = DM, 0, 1, 2$. Conditional on e_k, the individual likelihood function for the observed series $(t_{\min,DM}, t_{\max,DM}, ..., t_{\min,2}, t_{\max,2}, T)$ is obtained by integrating over all possible starting and ending values of t_{DM}, t_0, t_1, and t_2 :

$$L\left(t_{\min,DM}, ..., t_{\max,2}, T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right) =$$
$$\sum_{t_{DM}=t_{\min,DM}}^{\min\{t_{\max,DM},T\}} \Bigg[\sum_{\substack{t_0=\max\{t_{DM},t_{\min,0}\} \\ t_0 \geq t_{DM}}}^{\min\{t_{\max,0},T\}} \Bigg[\sum_{\substack{t_1=\max\{t_0,t_{\min,1}\} \\ t_1 \geq t_0}}^{\min\{t_{\max,1},T\}} \Bigg[\sum_{\substack{t_2=\max\{t_1,t_{\min,2}\} \\ t_2 \geq t_1}}^{\min\{t_{\max,2},T\}}$$
$$L\left(t_{DM}, t_0, t_1, t_2, T, \overrightarrow{DV}, \overrightarrow{d}\,|e_k, \mathbf{M}\right)\Bigg]\Bigg]\Bigg]. \tag{9}$$

These periods of time where we are uncertain about precisely when the individual progressed to the next disease stage constitute a key feature of this analysis. Not only is this an econometric issue that needs to be addressed; it is a real, substantive issue for analyzing disease progression and treatments. Numerous individuals will not recognize that they have progressed to DM or more advanced stages if they do not see a health care professional who can diagnose their condition. If the period of time where the disease is present but unobserved and untreated is long, then the individual may progress much more rapidly to more severe disease stages, possibly resulting in amputation or death. In our specification of the hazard functions we explicitly allow the duration of time a person spends with the disease without having been diagnosed to affect transitions to more advanced disease stages. This allows us to separate out whether or not more frequent diagnostic visits and the resulting earlier

treatments could actually slow down the disease progression from the aliasing that can occur only because more frequent diagnostic visits tend to lead to diagnoses at shorter durations of the disease stage. Diabetes is but one of many diseases where it is crucial to be able to separate the true effects of earlier treatments of a disease on outcomes from the spurious relationship between treatments and disease outcomes due to shorter intervals between diagnoses merely representing diagnoses at likely earlier (and unobserved) durations of the disease.

Finally, the unconditional log-likelihood function of the observed sample is:

$$L(\theta) = \sum_{i=1}^{N} \ln(\sum_{k=1}^{K} \Pr(e_k) L\left(t_{\min,DM_i}, ..., t_{\max,2_i}, T_i, \overrightarrow{DV}_i, \overrightarrow{d}_i | e_k, \mathbf{M}_i\right)), \quad (10)$$

where θ is the vector of parameters to be estimated, and $\Pr(e_k)$ is the probability of the discrete heterogeneity point e_k (Appendix A describes e_k, $\rho(e_k)$, and $\Pr(e_k)$ in more detail). To select the number of heterogeneity points (K), we use a likelihood ratio test as suggested in Mroz (1999). We add points of support with the corresponding additional parameters until the likelihood ratio test statistic fails to indicate improvement using a chi-squared distribution.

4 Data

We use data from the National Long-Term Care Survey (NLTCS) a longitudinal study of the elderly or persons aged 65 and older. The screening process began with a random sample of persons aged 65 and older in 1982. The respondents were tracked over time and more respondents were added to the sample in later waves (1989, 1994, 1999, and 2004).

Over the five cohorts of NLTCS, more than 40,000 individuals were followed, and screened interviews were drawn from this sampling frame. Medicare

claims data (Parts A & B), were merged with NLTCS data for all of these individuals by date and type of service. Diagnostic data were first added to Part B claims data in 1991. Furthermore, NLTCS respondents were merged with National Death Index data, providing the respondents death dates up to 2005.

Using the NLTCS and Medicare claims data from 1991 to 2004, we create a panel of individuals. We select individuals born between 1926 and 1939. This restriction ensures that all individuals are no older than 65 years of age when they enter the sample. We also drop individuals with less than two years (eight quarters) of data. Our final sample size consists of 10,059 individuals observed over a total of 221,962 quarters.

We divide the data into quarters of a year which correspond to time periods (t). In this analysis the longest period over which we observe an individual is 56 time periods. The first quarter of the year after the individual turns 65 is measured as time period 4 and thereafter every successive quarter is the next time period ($t+1$). For example, for a person who turns 65 in the first quarter of 1994, this period is $t = 4$ and the first quarter of 1996 is $t = 12$; for someone who turns 65 in the first quarter of 1996, this quarter is $t = 4$. The last period, which is the right censoring t, is the time period in which the individual either dies, has an amputation, or leaves the sample for some reason. We assume censoring not due to death or amputation is ignorable.

The first three time periods are reserved for calculating the probability of not acquiring DM prior to entering the sample. The time interval for these periods is arbitrary, but in our discussion we suppose that the first 3 time periods measure the previous 15 years before the age of 65 (5 year intervals as opposed to quarters).

5 Empirical Specification

There are 12 different equations in the likelihood function: two pre-age 65 hazards (DM and DNU_0), two post-age 65-before first visit hazards (DM and DNU_0), four post-age 65 and first visit hazards (DM, DNU_0, DNU_1, DNU_2), three visit equations (first general visit after turning age 65, subsequent general visits and podiatrist visits) and two health outcomes equations (amputation and death).

5.1 Dependent Variables

Stages: A person is in one of five mutually exclusive stages during a quarter. When a person transitions to a higher stage within a period, we consider the person to have been in the higher stage throughout the period.

Diabetes mellitus and all subsequent states are treated as absorbing states. Thus, if an individual entered the DM stage in time period t, s/he remains in that stage for the remainder of his or her life unless the person transitions to a more advanced state. Furthermore, an advanced stage of the disease automatically implies that all previous stages occurred. So if the same individual is diagnosed with a condition that would place her into stage 4 the first time she is observed in the data, she automatically acquires the three prior stages, albeit at times unknown to us.

Visits: We consider two types of visits: general and podiatrist. A podiatrist is a non-physician who specializes in diseases of the lower extremities. General visits include physician and podiatrist visits.

General Visits: A person was classified as having had a general visit during period t if s/he has a claim from any of the following: general practitioner (01), cardiologist (06), family practitioner (08), internal medicine specialist (11),

endocrinologist (46), clinical laboratory (69), or podiatrist (48).[5]

Podiatrist Visits: A person is classified as having a podiatrist visit in period t, if s/he had general visit in the period and had a claim from a podiatrist (48). Because a podiatrist claim also implies a general visit, a podiatrist visit must be interpreted as the additional effect of consulting a podiatrist over other health care visits included in general visits.

The main role of a health care visit in this analysis is to indicate the presence of DM, DNU_0, DNU_1, and DNU_2. Ideally any physician could provide this information; however, many visits are for other purposes, e.g., visits to a dermatologist or an oncologist (cancer specialist), and hence are not likely to include assessment of whether or not the patient has DM or its complications.

General and podiatrist visits capture the vast majority of visits devoted to the diagnosis and treatment of DM and its complications. The role of podiatrists in treating and making diagnoses increases with successively higher DNU stages. In our Medicare claims data, 81% of Medicare beneficiaries first received a diagnosis of DM from one of the general visit types listed above (excluding podiatrist); an additional 2.5% first received a diabetes diagnosis from a a podiatrist. The remainder (16.5%) of the diagnosis are made by other types of visits. For DNU_0 the corresponding percentages are 60.5% from general visits (excluding podiatrist) and 25.4% from podiatrist visits, while for DNU_1 the percentages are 34.5% from general visits and 48.3% from podiatrist visits. For DNU_2 the percentages are 22.9% from general visits and 58.4% from a podiatrist.

The dependent variable 'first visit' is a binary variable which equals one if the person has a general visit in a given time period after age 65. Once the individual has had a first visit after starting Medicare, we include a binary outcome variable visit in each period indicating whether or not there was a

[5] CPR codes are in parenthesis.

subsequent general visit. When the person had a general visit in a given period, we also include a binary variable for whether or not the person had a podiatrist claim in that period.

Health Shocks: In each period, the individual may experience two types of health shocks: a person's toe, foot, or leg is amputated and death. These are treated as censoring events.

Other health shocks associated with diabetes mellitus such as heart attacks and strokes were not included in order to reduce the number of estimable equations and because they do not affect higher transitions except for mortality which we model.

5.2 Explanatory Variables

Explanatory variables fall into four categories: (1) early diagnosis (our main explanatory variable); (2) demographic variables; (3) duration dependence; and (4) exclusion restrictions.

Early Diagnosis: The effects of early diagnosis are measured using two different type of controls. First, we include the time with undiagnosed DM, DNU_0, DNU_1, and DNU_2. These variables are defined as the difference in quarters between the time of the first visit with a diagnoses of the stage and the time when the stage began. For example, for a person who acquires DM in period 6 but only had a visit in period 10, time with undiagnosed DM equals 4. These variables are different from the duration of DM, DNU_0, DNU_1, and DNU_2 that we also control through duration dependence. If early diagnosis is beneficial, we expect to observe undiagnosed duration to have a positive effect on the probability of progression to the next stage and possibly a positive effect on mortality and amputation probabilities. Given the partial observability of the diabetes stage, the effect of these times with undiagnosed disease depend

critically on the integration implicit on equation (9).[6]

Second, we include binary variables for whether the person visited a general physician and a podiatrist during the last year lagged by six months. We distinguish between general and podiatrist visits because the marginal productivity may be different depending on the type of health professional that the person visited (Sloan et al., 2010). We expect these variables to have a negative effect on the probability of progression to a more severe stage, mortality and amputation. Because general visit includes a podiatrist visit, the podiatrist binary measures the additional effect of visiting a podiatrist on outcomes compare to a general visit.

Demographic Variables: We include binary variables for gender, educational attainment, marital status, arthritis, and race.[7] We also include a year trend and its square, and the year in which the individual become 65. These variables are used in all equations. We expect more highly educated and married persons to have better health outcomes. The year trend controls for the effects of age; older persons should experience increased probabilities of progression to higher stages, mortality, and amputation. The year in which the individual turns 65 controls for technological change and cohort effects. Generational changes in diets, for example, might affect diabetes outcomes.

Duration Dependence: Duration dependence is measured by a quadratic function of the time in quarters from the period the individual enters each of the stages (DM, DNU_0, DNU_1, and DNU_2). Duration dependence affects the probability of visits and health outcomes by shifting the intercept and by adding the effects of time with the condition. For example, an individual in stage 1 will have a given probability of visits. After acquiring DM, i.e., entering stage

[6] Mroz and Weir (1990) discuss identification of the distribution governing a partially observed process for a simpler model than that analyzed here.

[7] These variables were obtained from the NLTCS screener file using the latest available year.

2, we allow the intercept to shift and add time with DM as a regressor. We repeat these same steps for DNU_0, DNU_1, and DNU_2. Again, given the partial observability of the diabetes stage, the effect of duration dependence depends critically on the integration implicit on equation (9).

Exclusion Restrictions: We use distance to the nearest health professional as exclusion restrictions affecting doctor visits but not disease progression or health shocks. Distance is computed as the distance for each sample person from the center of the person's zip code of residence to the center of the zip code of each health care provider. For each individual we select the shortest distance to such providers. The NLTCS only provides area of residence information at the level of the primary sampling unit (PSU), which is a Standard Metropolitan Area for persons living in such areas and a rural area of a state for others. For each PSU, we compute the mean minimum distance to a provider for each Medicare beneficiary in the Medicare claims data. Thus, even for a large city, the mean minimum distance exceeds zero. Among PSUs, the mean minimum distance in miles to the nearest provider ranges from 0.02 to 12.03 for general visits and 0.17 to 80.88 for podiatrists. We expect an increase in the minimum distance to be negatively related to visits but not to affect disease progression or health shocks after controlling for visits.

6 Results

In our analysis sample, 3,488 of 10,059 individuals (34.6%) were diagnosed with DM (Table 2). Lower percentages, 10.2%, 5.3% and 3.5% transitioned to stages DNU_0, DNU_1 and DNU_2, respectively. The mean duration in the healthy stage ($no\ DM$) is 5.15 years with a mean total duration of 6.71 years in our data. For the 3,488 individuals who ever had DM, the mean duration with DM is 3.54 years and mean total duration in the sample is 7.29 years. For DNU_0, mean

durations are 1.53 and 7.73 years; for DNU_1, mean durations are 1.17 and 8.06 years; and for DNU_2, mean durations are 2.98 and 8.12 years.

The probabilities of observing death and amputation increase with diabetes disease progression. For a healthy individual, the lifetime probabilities of observing death and amputation are 0.05 and 0.005 while for an individual who progresses to DNU_2, the corresponding probabilities are 0.21 and 0.15. As the disease progresses the probabilities of general and podiatrist visits increase. On average, for each quarter the probability of a healthy individual visiting a general doctor is 0.47 and for a podiatrist is 0.03. For a person with DM, the probabilities are 0.59 and 0.06, while for a person with DNU_2, the probabilities are 0.66 and 0.32. Other health and treatment variables follow the expected pattern with respect to disease progression. However, it is difficult to place a causal interpretation on these simple summary statistics.

Tables 3 contains select coefficient estimates for our duration model with 8 points of support. We only report transition to diabetes and further complications after the first healthcare professional visit, outcomes (death and amputation), and general and podiatrist visits. The other transitions (pre age 65 outcomes and the first post age 65 doctor visit) were estimated but are not reported. We censor individuals who progressed to Stage 3 (DNU_0) by the time of their first post-age 65 doctor visit at the date of that visit. The model estimates the transition to DM, amputation, and death more precisely than transitions to DNU_0, DNU_1 and DNU_2. Appendix B reports estimates with no heterogeneity controls.

The time with undiagnosed DM has a positive and significant impact on the transitions to the onset of DNU_0, amputation, and death. This implies that early diagnosis of DM can delay complications associated with DM. The effects of unobserved DM duration on the hazards for DNU_1 and DNU_2, how-

ever, are not significant and have the opposite sign. These insignificant effects are consistent with the hypothesis that once one progress beyond DM that the harmful effects from uncontrolled DM are captured completely by the event of having progressed to a more severe stage. Also once the individual makes the transition to DM, time with undiagnosed DNU_0 and DNU_1 have negative effects on the onset of further lower extremity complications (opposite signs to our expectations). However, as discussed below, duration dependence for DNU_0 and DNU_1 is very large and positive for these transitions to further complications, implying that once an individual contracts DNU_0, s/he will transition very rapidly to DNU_1 and DNU_2. It is hard to identify the effects of time with undiagnosed DNU_0 and DNU_1 because people spent little time in these more severe stages and visited the doctor more often (see Table 2).

General visits (estimated with a six months lag) are not effective in delaying the onset of DNU_0, DNU_1 and DNU_2; nor do they delay amputation or death. On the other hand, podiatrist visits are productive in delaying amputation and the coefficients always have the expected sign. This result is consistent with the reduced form findings of Sloan et al. (2010).

Across all transition probabilities, the estimates of the quadratic duration dependence function imply a U-shape between the probability of transitioning to the next stage or outcome and time with DM, DNU_0, DNU_1 and DNU_2. However, the bottom of the U is reached very quickly for most outcomes, implying positive duration dependence thereafter. Once an individual transitions to DNU_0 the probability of progressing to DNU_1 increases substantially with time. The effect is even larger when analyzing the DNU_1 duration dependence on the transition to DNU_2. These effects are consistent with the fact that individuals spend a short time in DNU_0 or DNU_1 stages. As expected, having DM and/or DNU_0 have large positive effects on the probability of death and

having DNU_1 and/or DNU_2 has a large positive effect on the probability of amputation.

Other variables, in general, have the expected effects. Non-whites and males have higher probabilities of transition to DM and DNU_1. These imply that non-whites and males are more likely to acquire diabetes at an earlier age. Males are also more likely to die and have an amputation. Individuals with high school or better education are associated with a lower probability of progressing to DM and have lower mortality probabilities. Married persons have lower transitions to DM and lower amputation probabilities. Older individuals (time and time squared) have higher transitions to DM and DNU_2 after the ages of 71 and 72.

Individuals who turned 65 in later years have higher transition probabilities to DM and DNU_0, but lower transition probabilities to DNU_1 and lower mortality. This result is consistent with finding of increasing rates of diabetes in younger cohorts but at the same time improvements in mortality. A plausible explanation is the increased rate of diabetes are due to changes in diets and improvement in mortality are due to health care technological improvements.

The main determinants of the probability of having a general visit are male (-), better education (-), marriage (+), age (+), arthritis (+), year the person become 65 (+), having DM (+), having DNU_0 (+), and having DNU_2 (+). Both exclusion restrictions (distance to general health professional and podiatrist) are significant, but have a positive effect of visits, which was unexpected. The main determinants of podiatrist visits are white (+), male (-), better education (+), age (+), arthritis (+), having DM (-), having DNU_0 (+), and having DNU_1 (+). Podiatrist distance (our main instrument) has the expected sign and the coefficient is highly significant. When we did not control for heterogeneity (Appendix B) both distance to general health professionals and podiatrists have the expected sign (negative) and they are highly significant in

both equations.

Tables 4 shows the heterogeneity points of support for the different transitions and the implied probabilities for each of the eight points of support. Using a likelihood ratio, we rejected models with fewer points of support including the model with no heterogeneity. The probabilities associated with the mass points range from 0.0219 to 0.2391 which indicates that there is no point with a very small or very large weight. Also, there are no extreme mass points for any of the specifications.

The implied correlation between the heterogeneities points of the different equations seem plausible (Table 5) and often they are quite substantial. The unobserved factors are mostly positively related across outcomes. The exception is that the unobserved factors affecting DNU_2 are negatively correlated with those for all of the other outcomes.

Early diagnosis and presumably treatment of DM affects progressing to worse stages, death, and amputation through several channels and in a complex manner. Calculating marginal effects of early diagnosis is not straightforward. To better gauge the effects of early diagnosis on progression to worse stages we simulated our model based on our estimates of the parameters for an "average individual" of the exogenous variables: white, male, education, marriage, year the person become 65, arthritis, the average distance to the nearest doctor, and the average distance to the nearest podiatrist. The individual was assumed to be healthy at the time of his first visit at time period 4 (thus we did not use the pre 65 and pre first visit equations). Using our hazard functions we simulated the probability of contracting diabetes, dying, or having an amputation for each period after period 4 for two different individuals. One who visits the doctor every six month and another who visits the doctor once a year until they are diagnosed with diabetes. Once they contract diabetes we simulate subsequent

visits, worse stages, and outcomes using the appropriate hazard functions. We found that a person who visited the doctor at a six month intervals during those early years was able delay the onset of diabetic neuropathy by 0.14 quarters, mortality by 0.15 quarters, and amputation by 0.12 quarters, roughly two weeks each.[8] From a policy point of view, the value of delaying death by two weeks could easily exceed the cost of having just one more doctor visit each year.

7 Conclusion and Extensions

This study develops and estimates a discrete multiple state duration model that allows for duration dependence, unmeasured heterogeneity, partially observed states, and endogenous treatment. The model is well suited for obtaining causal effects of time-varying explanatory variables on the duration of a given state, future states, and exit from the condition under the presence of omitted variable bias. To our knowledge, our study is the first to allow for endogenous time-varying explanatory variables in the context of multiple state duration models.

We apply this model to the study of the progression of diabetic neuropathy, which are serious complications of the lower extremities associated with diabetes. Diabetic neuropathy can progress through several stages of increasing severity. If untreated, it may lead to an amputation of a toe, a foot, or part of a leg or even death. Given limitations of randomized controlled trials, including the high cost of following-up individuals over a lengthy time span, since complications of diabetes often develop slowly, econometric models that allow measurement of the effectiveness of these treatments are crucial to better treating the disease.

An important feature of our model is that it allows us to distinguish true effects of earlier treatment of a disease on outcomes from the spurious relation-

[8] These marginal effects are based on 10,000 simulations.

ship between treatments and disease outcomes by merely diagnosing the disease earlier. Diabetes is not the only disease where it is crucial to separate these effects. This problem is called "lead bias" in the medical literature and it is widely recognized as clouding the true effects of screening tests on delaying the progression of different cancers.

Our results show that duration dependence is positive for every stage of diabetes. The longer an individual has the disease the more likely s/he is to transition to a more severe stage or leave the sample because of death or amputation. However, our results also show that the longer a person has diabetes without having being diagnosed (and treated) further increases the probabilities of transitioning to a worse stage, death or amputation. Thus, our results are consistent with the hypothesis that earlier treatment of diabetes is effective in delaying complications after controlling for the length of time the individual have diabetes. We found that a person who visited the doctor at six month intervals instead of once a year during her/his early years was able to delay the onset of diabetic neuropathy, mortality, and amputation roughly by two weeks. From a policy point of view, the value of delaying death by two weeks could easily exceed the cost of having just one more doctor visit each year.

We acknowledge several limitations. First, we define treatment as visiting the doctor (either general visit or podiatrist visit) but we do not know the exact content of the visit. Thus, for example, since the claims data do not contain information on prescribed drugs, we cannot assess whether a particular prescription drug is effective. Nor do we know if the doctor advised the patient to stop smoking or increase physical activity. Second, we do not measure individual behaviors of individuals with diabetes, such as better control of blood glucose through diet and exercise, which also may affect the progression of diabetes. However, because we allow for unmeasured heterogeneity, not controlling for

individual behaviors will not affect the consistency of our treatment variables. These two caveats are limitations of our data since our model can be extended to control for individual behaviors and different treatments. Third, our unmeasured heterogeneity is time invariant within each equation in the econometric model. A potential extension is to interact the unmeasured heterogeneity term with age to allow changing as the individual becomes older.

Overall, the approach is promising for evaluating causal effects with administrative data from a variety of contexts, ranging from medical to educational to job training programs.

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References

[1] Abbring, J. and J. Heckman, 2008, Dynamic policy evaluation, in: Matyas, L. and P. Sevestre (Eds.), The Econometrics of Panel Data, 3rd edition. Kluwer Academic Publishers, Dordrecht.

[2] Abbring, J. and G.J. van den Berg, 2003, The nonparametric identification of treatment effects in duration models. Econometrica 71(5), 1491–1517.

[3] Bhattacharya J., 2005, Specialty selection and lifetime returns to specialization within medicine. Journal of Human Resources 40(1), 115-141.

[4] Cole P and AS Morrison, 1980, Basic issues in population screening for cancer. Journal of the National Cancer Institute 64(5), 1263-72.

[5] Cunha F. and J. Heckman, 2007, The Technology of Skill Formation. American Economic Review 97(2), 31–47.

[6] Garces E., D. Thomas, and J. Currie, 2002, Longer-Term Effects of Head Start. American Economic Review 92(4), 999–1012.

[7] Gill, R.D. and J.M. Robins, 2001, Causal inference for complex longitudinal data: the continuous case. The Annals of Statistics 29(6), 1785–1811.

[8] Glewwe P. and H. Jacoby, 2004, Economic growth and the demand for education: is there a wealth effect? Journal of Development Economics 74(1), 33-51.

[9] Heckman JJ, and S. Navarro, 2007, Dynamic discrete choice and dynamic treatment effects. Journal of Econometrics 136, 341-396.

[10] Heckman J., B. Singer, 1984, A method for minimizing the impact of distributional assumptions in econometric models for duration data. Econometrica 52(2), 271-320.

[11] Kiefer N., 1988, Economic Duration Data and Hazard Functions. Journal of Economic Literature XXVI 646-679.

[12] Lancaster T., 1990, The Econometrics Analysis of Transition Data. Cambridge: Cambridge University Press.

[13] Lechner, M. and C. Wunsch, 2009, Are training programs more effective when unemployment is high?, Journal of Labor Economics 27(4), 653-692

[14] Liu H, TA Mroz and L Adair, 2009, Parental compensatory behaviors and early child health outcomes in Cebu, Philippines, Journal of Development Economics 90(2), 209-230.

[15] Liu H, T.A. Mroz and W. van der Klaauv, 2010, Maternal Employment, Migration, and Child Development. Journal of Econometrics 156(1):212-228.

[16] Llobera J, M Esteva, J Rifà, E Benito, J Terrasa, C Rojas, O Pons, G Catalán, A Avellà, 2000, Terminal cancer. duration and prediction of survival time. *Eur J Cancer* 36(16), 2036-43.

[17] Montori V, Y. Wang, P. Alonso-Coello, and S. Bhagra, 2006, Systematic evaluation of the quality of randomized controlled trials in diabetes. Diabetes Care 29(8), 1833-1838.

[18] Mroz, TA., 1999, Discrete factor approximations in simultaneous equation models: Estimating the impact of a dummy endogenous variable on a continuous outcome. Journal of Econometrics 92, 233-274.

[19] Mroz, TA and T Savage, 2006, The Long-Term Effects of Youth Unemployment. The Journal of Human Resources 41(2): 259-293.

[20] Mroz, TA. and D. Weir, 1990, Structural Change in Life Cycle Fertility During the Fertility Transition: France Before and After the Revolution of 1789. Population Studies 44, 61-87.

[21] Picone G., F. Sloan, and D. Brown, 2004, Do Routine Eye Exams Improve Vision? International Journal of Health Care Finance and Economics 4(1), 43-63.

[22] Richardson, K. and G. van den Berg, 2008, Duration dependence versus unobserved heterogeneity in treatment effects: Swedish labor market training and the transition rate to employment." Institute for Labor Market Policy Evaluation, Working Paper.

[23] Robins, J.M., 1989, The analysis of randomized and non-randomized AIDS treatment trials using a new approach to causal inference in longitudinal studies, in: Sechrest, L., Freeman, H., Mulley, A. (Eds.), *Health Services Research Methodology: A Focus on AIDS*, National Center for Health Services Research and Health Care Technology Assessment, Rockville, MD, pp. 113–159.

[24] Robins, J.M., 1997, Causal inference from complex longitudinal data, in: Berkane, M. (Ed.), *Latent Variable Modeling and Applications to Causality*, Lecture Notes in Statistics. Springer, New York, pp. 69–117.

[25] Sloan, FA., A. Bethel, D. Ruiz jr. et. al., 2008, The growing burden of diabetes mellitus in the US elderly population. Archives of Internal Medicine 168(2), 192-199.

[26] Sloan, FA., M. Feinglos, and D. Grossman, 2010, Receipt of care and reduction of lower extremity amputations in a nationally representative sample of U.S. elderly. Health Service Research 45(6), 1740-1762.

[27] van den Berg G.J., 2001, Duration Models: Specification, Identification, and Multiple Durations, in JJ Heckman and E Leamer (Ed.), *Handbook of Econometrics*, Vol. V, Ch. 55, 3381-3460.

8 Appendix

8.1 Likelihood Function

Conditional on e_k; the likelihood function for an individual that did not progress to DM by the last observation T is given by

$$L_{nDM}\left(T|\mathbf{M}, e_k\right) = Sur\left(DM = T\right) \times \Pr\left(DV_T\right) \times \Pr\left(d_T\right)$$

where

$$\begin{aligned} Sur\left(DM = T\right) &= \prod_{t=1}^{T}\left(1 - h_t^{DM}\left(X_t^{DM}, e_k\right)\right) \\ \Pr\left(DV_T^{nDM}\right) &= \prod_{t=4}^{T}\Pr\left(DV_t\left(Z_t, e_k\right)\right) \\ \Pr\left(d_T^{nDM}\right) &= \prod_{t=4}^{T}\Pr\left(d_t\left(W_t, e_k\right)\right) \end{aligned}$$

where $Sur\left(DM = T\right)$ is the probability of an individual surviving to T without DM, $\Pr\left(DV_T^{nDM}\right)$ is the probability of a sequence of doctor visits for an individual who never have DM, and $\Pr\left(d_T^{nDM}\right)$ is the probability of a sequence of discrete outcomes for an individual who never have DM.

The likelihood function for an individual that progressed to DM at t_{DM} and did not progressed to DNU_0 by T is given by

$$L_{DM}\left(t_{DM}, T|\mathbf{M}, e_k\right) = \Pr\left(DM = t_{DM}\right) \times Sur\left(DNU_0 = T\right) \times \Pr\left(DV_T\right) \times \Pr\left(d_T\right)$$

where

$$\begin{aligned}
\Pr\left(DM_t = t_{DM}\right) &= h_{t_{DM}}^{DM}\left(X_t^{DM}, e_k\right) \prod_{t=1}^{t_{DM}-1}\left(1 - h_t^{DM}\left(X_t^{DM}, e_k\right)\right) \\
Sur\left(DNU_0 = T\right) &= \prod_{t=t_{DM}}^{T}\left(1 - h_t^{DNU_0}\left(t^{DM}, X_t^{DNU_0}, e_k\right)\right) \\
\Pr\left(DV_T^{DM}\right) &= \prod_{t=4}^{t_{DM}} \Pr\left(DV_t\left(Z_t, e_k\right)\right) \prod_{t=t_{DM}+1}^{T} \Pr\left(DV_t\left(t^{DM}, Z_t, e_k\right)\right) \\
\Pr\left(d_T^{DM}\right) &= \prod_{t=4}^{t_{DM}} \Pr\left(d_t\left(W_t, e_k\right)\right) \prod_{t=t_{DM}+1}^{T} \Pr\left(d_t\left(t^{DM}, W_t, e_k\right)\right)
\end{aligned}$$

where $\Pr\left(DM_t = t_{DM}\right)$ is the probability of an individual contracting DM at period t_{DM}, $Sur\left(DNU_0 = T\right)$ is the probability of an individual surviving to T without DNU_0, $\Pr\left(DV_T^{DM}\right)$ is the probability of a sequence of doctor visits for an individual who contracted DM at time t_{DM} and never have DNU_0, and $\Pr\left(d_T^{DM}\right)$ is the probability of a sequence of discrete outcomes for an individual who contracted DM at time t_{DM} and never had DNU_0.

The likelihood function that progressed to DM at t_{DM}, progressed to DNU_0 at t_0, and did not progressed to DNU_1 by T is given by

$$\begin{aligned}
L_{DNU_0}\left(t_{DM}, t_0, T|\mathbf{M}, e_k\right) &= \Pr\left(DM = t_{DM}\right) \times \Pr\left(DNU_0 = t_0\right) \\
&\quad \times Sur\left(DNU_1 = T\right) \times \Pr\left(DV_T\right) \times \Pr\left(d_T\right)
\end{aligned}$$

where

$$
\begin{aligned}
\Pr\left(DNU_0 = t_0\right) &= h_t^{DNU_0}\left(t^{DM}, X_t^{DNU_0}, e_k\right) \prod_{t=t_{DM}}^{t_0-1}\left(1 - h_t^{DNU_0}\left(t^{DM}, X_t^{DNU_0}, e_k\right)\right) \\
Sur\left(DNU_1 = T\right) &= \prod_{t=t_0}^{T}\left(1 - h_t^{DNU_1}\left(t^{DM}, t^o, X_t^{DNU_1}, e_k\right)\right) \\
\Pr\left(DV_T^{DNU_0}\right) &= \prod_{t=4}^{t_{DM}} \Pr\left(DV_t\left(Z_t, e_k\right)\right) \prod_{t=t_{DM}+1}^{t_0} \Pr\left(DV_t\left(t^{DM}, Z_t, e_k\right)\right) \prod_{t=t_0+1}^{T} \Pr\left(DV_t\left(t^0, t^{DM}, Z_t, e_k\right)\right) \\
\Pr\left(d_T^{DNU_0}\right) &= \prod_{t=4}^{t_{DM}} \Pr\left(d_t\left(W_t, e_k\right)\right) \prod_{t=t_{DM}+1}^{t_0} \Pr\left(d_t\left(t^{DM}, W_t, e_k\right)\right) \prod_{t=t_0+1}^{T} \Pr\left(d_t\left(t^0, t^{DM}, Z_t, e_k\right)\right)
\end{aligned}
$$

where $\Pr\left(DNU_0 = t_0\right)$ is the probability of an individual contracting DNU_0 at period t_0, $Sur\left(DNU_1 = T\right)$ is the probability of an individual surviving to T without DNU_1, $\Pr\left(DV_T^{DNU_0}\right)$ is the probability of a sequence of doctor visits for an individual who contracted DM at time t_{DM}, DNU_0 at time t_0, and never have DNU_1, and $\Pr\left(d_T^{DNU_0}\right)$ is the probability of a sequence of discrete outcomes for an individual who contracted DM at time t_{DM}, DNU_0 at time t_0, and never have DNU_1.

The likelihood function for an individual that progressed to DM at t_{DM}, progressed to DNU_0 at t_0, progressed to DNU_1 at t_1, and did not progressed to DNU_2 by T is given by

$$
\begin{aligned}
L_{DNU_1}\left(t_{DM}, t_0, t_1, T|\mathbf{M}, e_k\right) &= \Pr\left(DM = t_{DM}\right) \times \Pr\left(DNU_0 = t_0\right) \times \Pr\left(DNU_1 = t_1\right) \\
&\quad \times Sur\left(DNU_2 = T\right) \times \Pr\left(DV_T\right) \times \Pr\left(d_T\right)
\end{aligned}
$$

where

$$\begin{aligned}
\Pr\left(DNU_1 = t_1\right) &= h_t^{DNU_1}\left(t^{DM}, t^o, X_t^{DNU_1}, e_k\right)\prod_{t=t_0}^{t_1-1}\left(1 - h_t^{DNU_1}\left(t^{DM}, t^o, X_t^{DNU_1}, e_k\right)\right) \\
Sur\left(DNU_2 = T\right) &= \prod_{t=t_1}^{T}\left(1 - h_t^{DNU_2}\left(t^{DM}, t^o, t^1, X_t^{DNU_2}, e_k\right)\right) \\
\Pr\left(DV_T^{DNU_1}\right) &= \prod_{t=4}^{t_{DM}}\Pr\left(DV_t\left(Z_t, e_k\right)\right)\prod_{t=t_{DM}+1}^{t_0}\Pr\left(DV_t\left(t^{DM}, Z_t, e_k\right)\right) \\
&\quad \prod_{t=t_0+1}^{t_1}\Pr\left(DV_t\left(t^{DM}, t^o, Z_t, e_k\right)\right)\prod_{t=t_1+1}^{T}\Pr\left(DV_t\left(t^{DM}, t^o, t^1, Z_t, e_k\right)\right) \\
\Pr\left(d_T^{DNU_1}\right) &= \prod_{t=4}^{t_{DM}}\Pr\left(d_t\left(W_t, e_k\right)\right)\prod_{t=t_{DM}+1}^{t_0}\Pr\left(d_t\left(t^{DM}, W_t, e_k\right)\right) \\
&\quad \prod_{t=t_0+1}^{t_1}\Pr\left(d_t\left(t^{DM}, t^o, Z_t, e_k\right)\right)\prod_{t=t_1+1}^{T}\Pr\left(d_t\left(t^{DM}, t^o, t^1, Z_t, e_k\right)\right)
\end{aligned}$$

where $\Pr\left(DNU_1 = t_1\right)$ is the probability of an individual contracting DNU_1 at period t_1, $Sur\left(DNU_2 = T\right)$ is the probability of an individual surviving to T without DNU_2, $\Pr\left(DV_T^{DNU_1}\right)$ is the probability of a sequence of doctor visits for an individual who contracted DM at time t_{DM}, DNU_0 at time t_0, DNU_1 at time t_1, and never have DNU_2, and $\Pr\left(d_T^{DNU_1}\right)$ is the probability of a sequence of discrete outcomes for an individual who contracted DM at time t_{DM}, DNU_0 at time t_0, DNU_1 at time t_1, and never have DNU_2.

Finally, the likelihood function for an individual that progressed to DM at t_{DM}, progressed to DNU_0 at t_0, progressed to DNU_1 at t_1, and progressed to DNU_2 at t_2 is given by

$$\begin{aligned}
L_{DNU_2}\left(t_{DM}, t_0, t_1, t_2|\mathbf{M}, e_k\right) &= \Pr\left(DM = t_{DM}\right) \times \Pr\left(DNU_0 = t_0\right) \times \Pr\left(DNU_1 = t_1\right) \\
&\quad \times \Pr\left(DNU_2 = t_2\right) \times \Pr\left(DV_T\right) \times \Pr\left(d_T\right)
\end{aligned}$$

where

$$\begin{aligned}
\Pr\left(DNU_2 = t_2\right) &= h_t^{DNU_2}\left(t^{DM}, t^o, t^1, X_t^{DNU_2}, e_k\right)\prod_{t=t_2}^{t_2-1}\left(1 - h_t^{DNU_1}\left(t^{DM}, t^o, t^1, X_t^{DNU_2}, e_k\right)\right) \\
\Pr\left(DV_T^{DNU_2}\right) &= \prod_{t=4}^{t_{DM}}\Pr\left(DV_t\left(Z_t, e_k\right)\right)\prod_{t=t_{DM}+1}^{t_0}\Pr\left(DV_t\left(t^{DM}, Z_t, e_k\right)\right)\prod_{t=t_0+1}^{t_1}\Pr\left(DV_t\left(t^{DM}, t^o, Z_t, e_k\right)\right) \\
&\quad \prod_{t=t_1+1}^{t_2}\Pr\left(DV_t\left(t^{DM}, t^o, t^1, Z_t, e_k\right)\right)\prod_{t=t_2+1}^{T}\Pr\left(DV_t\left(t^{DM}, t^o, t^1, t^2, Z_t, e_k\right)\right) \\
\Pr\left(d_T^{DNU_2}\right) &= \prod_{t=4}^{t_{DM}}\Pr\left(d_t\left(W_t, e_k\right)\right)\prod_{t=t_{DM}+1}^{t_0}\Pr\left(d_t\left(t^{DM}, W_t, e_k\right)\right)\prod_{t=t_0+1}^{t_1}\Pr\left(d_t\left(t^{DM}, t^o, Z_t, e_k\right)\right) \\
&\quad \prod_{t=t_1+1}^{t_2}\Pr\left(d_t\left(t^{DM}, t^o, t^1, Z_t, e_k\right)\right)\prod_{t=t_2+1}^{T}\Pr\left(d_t\left(t^{DM}, t^o, t^1, t^2, Z_t, e_k\right)\right)
\end{aligned}$$

where $\Pr\left(DNU_2 = t_2\right)$ is the probability of an individual contracting DNU_2 at period t_2, $\Pr\left(DV_T^{DNU_2}\right)$ is the probability of a sequence of doctor visits for an individual who contracted DM at time t_{DM}, DNU_0 at time t_0, DNU_1 at time t_1, and never have DNU_2, and $\Pr\left(d_T^{DNU_1}\right)$ is the probability of a sequence of discrete outcomes for an individual who contracted DM at time t_{DM}, DNU_0 at time t_0, DNU_1 at time t_1, and DNU_2 at time t_2.

8.2 Unmeasured Heterogeneity

For each of the events we assume a discrete heterogeneity distribution which is model as a polynomial

$$\begin{aligned}
\rho_o\left(e_k\right) &= \rho_{o1}\left(\frac{k-1}{K-1}\right) + ... + \rho_{oJ}\left(\frac{k-1}{K-1}\right)^{J_0} \\
k &= 1, ..., K \text{ and } J_0 \leq K-1
\end{aligned}$$

where $o = DM$, DNU_0, DNU_1, DNU_2, d, and DV; and K is the number of heterogeneity points. We estimate $\Pr\left(e_k\right)$ subject to the restrictions that each probability is non-negative and $\sum_{k=1}^{K}\Pr\left(e_k\right) = 1$.

TABLE 1: DISEASE PROGRESSION

STAGE	PROGRESSION	CONDITION	ICD9 CODE
1	Healthy		
2	Diabetes Mellitus (DM)	Diabetes Mellitus	250.xx
3	Lower Extremity Complication (DNU_0)	Neuropathy	250.6 357.2 355.xx
		Paresthesia	782.xx
		Pain in Feet	729.5
		Diabetic Amyotrophy	358.1
4	Lower Extremity Complication (DNU_1)	Cellulites	681.1 682.6 682.7
		Charcot Foot	0707.10
5	Lower Extremity Complication (DNU_2)	Osteomyelitis	730.06 730.07 730.16 730.17 730.26 730.27
		Gangrene	250.7 785.4

TABLE 2: SUMMARY STATISTICS

	PROGRESSION				
	Healthy	**DM**	**DNU_0**	**DNU_1**	**DNU_2**
Number of Individuals Ever Observed**	10,059	3,488	1,026	535	368
Duration in Years Before Exit**	6.71	7.29	7.73	8.06	8.12
(s.d.)	(3.65)	(6.26)	(7.41)	(7.88)	(8.00)
Duration in Stage in Years Before Exit**	5.15	3.54	1.53	1.17	2.98
(s.d.)	(3.84)	(3.33)	(1.60)	(1.23)	(2.96)
Death (%)*	4.97	8.20	8.28	6.92	21.20
Amputation (%)*	0.48	0.43	0.10	0.11	14.67
Arthritis (%)**	7.11	10.67	13.26	14.77	16.03
Quarters with a General Practitioner Visit (%)*	46.64	59.33	69.23	66.59	46.35
Quarters with a Podiatrist Visit (%)*	3.29	6.02	13.41	25.96	32.51
White (%)**	86.72	81.62	79.14	77.20	77.45
Male (%)**	45.58	49.00	46.78	49.72	50.54
Married (%)**	56.77	53.41	51.56	49.53	51.63
Education (%)**	48.53	43.18	41.81	39.63	40.22
Year Turned 65*	1997.0	1996.5	1996.5	1995.5	1995.0
(s.d.)	(3.62)	(3.57)	(2.42)	(3.28)	(3.18)

* Based on the number of individuals that exit the data-set in the stage.

**Based on the number of individuals in the stage or greater.

TABLE 3: RESULTS WITH EIGHT POINTS HETEROGENEITY

Explanatory Variable	DISEASE[1]				OUTCOMES		VISITS	
	DM	DNU_0	DNU_1	DNU_2	DEATH	AMPUTATION	GENERAL	PODIATRIST
EARLY DIAGNOSIS								
Time with undiagnosed DM		0.0194***	-0.0114	-0.0082	0.0191***	0.9664*		
		(0.0065)	(0.0091)	(0.0105)	(0.0057)	(0.5753)		
Time with undiagnosed DNU_0			-0.2308*	-0.0658	0.0863	-0.1101		
			(0.1224)	(0.1160)	(0.0860)	(0.1921)		
Time with undiagnosed DNU_1				-0.1285*	-0.2847	-0.0737		
				(0.0743)	(0.2576)	(0.1408)		
Time with undiagnosed DNU_2					0.0042	-0.0019		
					(0.0074)	(0.0100)		
One Year General Visit (6 month lag)		-0.0241	-0.2071	0.6011**	-0.0760	0.4068		
		(0.1351)	(0.2181)	(0.2945)	(0.1077)	(0.3519)		
One Year Podiatrist Visit (6 month lag)				-0.1543	-0.1418	-0.5703*		
				(0.2056)	(0.1226)	(0.3087)		
OTHER VARIABLES[2]								
Constant	-4.2078***	-4.2985***	0.1761	0.5229	-8.9968***	-9.1675***	-1.7798***	-4.1576***
	(0.1399)	(0.3222)	(0.5317)	(0.6689)	(0.2867)	(0.7125)	(0.0549)	(0.1097)
White	-0.4345***	-0.0252	-0.2382*	0.0051	0.1053	0.1057	0.0134	0.3665***
	(0.0637)	(0.0854)	(0.1314)	(0.1744)	(0.0916)	(0.2501)	(0.0352)	(0.0762)
Male	0.2956***	-0.0757	0.2075*	-0.0085	0.2273***	0.6646***	-0.2969***	-0.5002***
	(0.0464)	(0.0698)	(0.1091)	(0.1445)	(0.0676)	(0.1953)	(0.0248)	(0.0430)
High School or Better	-0.2531***	-0.0323	-0.1563	-0.0401	-1.2249***	-0.2773	-0.0624*	0.3627***
	(0.0621)	(0.0874)	(0.1366)	(0.1787)	(0.1233)	(0.2539)	(0.0343)	(0.0640)
Married	-0.1434***	0.0476	-0.0427	0.1595	0.0042	-0.5780***	0.0884***	-0.0371
	(0.0517)	(0.0769)	(0.1243)	(0.1624)	(0.0900)	(0.2185)	(0.0279)	(0.0461)
Time – Age (in quarters)	-0.0484***	-0.0169	0.0111	-0.0779**	0.1145***	0.0021	0.0076***	0.0343***
	(0.0074)	(0.0171)	(0.0271)	(0.0352)	(0.0147)	(0.0389)	(0.0019)	(0.0039)
Time Square	0.0009***	0.0003	-0.0005	0.0013**	-0.0010***	0.0002	0.0004***	-0.0001
	(0.0001)	(0.0003)	(0.0004)	(0.0006)	(0.0002)	(0.0006)	(0.0000)	(0.0001)
Arthritis	0.3189***	-0.0045	-0.1464	0.0189	-0.0597	0.4096	0.4557***	0.4600***
	(0.0928)	(0.1259)	(0.1889)	(0.2354)	(0.1202)	(0.3172)	(0.0403)	(0.0555)
Year that a person becomes 65 (1991=0.1, 1992=0.2, …)	0.4887***	0.5299***	-1.0709***	-0.2655	-0.2438	0.4507	0.5912***	0.0305
	(0.0789)	(0.1197)	(0.1889)	(0.2577)	(0.1492)	(0.3445)	(0.0383)	(0.0713)
EXCLUSION RESTRICTIONS								
Weighted average distance to general doctor							0.2830***	
							(0.0622)	
Weighted average distance to podiatrist							0.0357***	-0.1499***
							(0.0117)	(0.0197)
DURATION DEPENDENCE								
Contracted DM					0.5442***	-0.3731	0.3074***	-0.2666***
					(0.1064)	(0.3426)	(0.0255)	(0.0458)
Time with DM		-0.0268***	-0.0177	-0.0215	-0.0205***	-0.0028		0.0263***
		(0.0084)	(0.0116)	(0.0143)	(0.0064)	(0.0142)		(0.0018)
Time with DM Square		0.0195***	0.0209**	0.0185**				
		(0.0067)	(0.0082)	(0.0079)				
Contracted DNU_0					1.0438***	-1.0494	0.6626***	0.7235***
					(0.1692)	(1.0331)	(0.0691)	(0.0759)
Time with DNU_0			-0.4490***	-0.0472	-0.0354***	0.0276		-0.0414***
			(0.0257)	(0.0381)	(0.0140)	(0.0202)		(0.0069)
Time with DNU_0 Square			0.4406***	0.0852				
			(0.0302)	(0.0615)				
Contracted DNU_1					-0.2403	2.7808**	-0.1441	1.2582***
					(0.2872)	(1.1079)	(0.1152)	(0.1206)
Time with DNU_1				-0.5516***	0.0411*	-0.0140		-0.0630***
				(0.0486)	(0.0216)	(0.0329)		(0.0106)
Time with DNU_1 Square				0.4274***				
				(0.0688)				
Contracted DNU_2					0.2298	2.6540***	0.4692***	-0.0222
					(0.2973)	(0.5063)	(0.1172)	(0.1249)
Time with DNU_2					0.0120	-0.1417***		0.0527***
					(0.0209)	(0.0397)		(0.0104)
Log Likelihood	-198,314.52666							

***significant at 0.01 level ***significant at 0.05 level *significant at 0.1 level

1 Several Equations described in the text were estimated but are not reported. They include: two pre-age 65 hazards – DM and DNU0 ; two post-age 65-before first visit hazards – DM and DNU0 ; the transition to DM post-age 65-post first visit and the first doctor visit.

2 We also control for high school or better missing, marital status missing, and general visit continuity missing.

TABLE 4: HETEROGENEITY FOR EIGHT POINTS OF SUPPORT

Point of Support	Probability	DISEASE[1]				OUTCOMES			
		DM	DNU_0	DNU_1	DNU_2	DEATH	AMPUTATION	GENERAL	PODIATRIST
1	0.1387	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.2391	0.3364	-0.1844	-0.5650	-0.2256	0.7692	-0.1013	1.3772	-2.6573
3	0.1652	0.7474	0.0748	-0.5598	-0.3936	1.2527	0.0267	2.7762	-1.9580
4	0.1131	1.1216	0.5420	-0.2257	-0.4776	1.4766	0.2635	3.8712	0.4933
5	0.0262	1.3470	0.9817	0.1958	-0.4515	1.4672	0.4883	4.3363	3.0921
6	0.0219	1.3122	1.1583	0.4634	-0.2891	1.2505	0.5805	3.8457	4.2340
7	0.0747	0.9053	0.8362	0.3357	0.0358	0.8527	0.4195	2.0735	2.3144
8	0.2211	0.0147	-0.2202	-0.4287	0.5495	0.2999	-0.1154	-1.3060	-4.2712
Expected Value		0.4656	0.0944	-0.3076	-0.0670	0.7537	0.0413	1.2896	-1.5010
Standard Deviation		0.4374	0.3885	0.3067	0.3649	0.4940	0.1960	1.8092	2.2745

TABLE 5: CORRELATION FOR EIGHT POINTS OF SUPPORT

	DM	DNU_0	DNU_1	DNU_2	DEATH	AMPUTATION	GENERAL	PODIATRIST
DM	1.0000							
DNU0	0.8412	1.0000						
DNU1	0.3098	0.7708	1.0000					
DNU2	-0.7281	-0.4327	0.0182	1.0000				
DEATH	0.9220	0.5680	-0.0824	-0.7700	1.0000			
AMPUTATION	0.8309	0.9998	0.7826	-0.4206	0.5524	1.0000		
GENERAL	0.9397	0.6989	0.1660	-0.9186	0.9171	0.6869	1.0000	
PODIATRIST	0.6829	0.9102	0.8424	-0.5214	0.3726	0.9134	0.6509	1.0000

APPENDIX B: RESULTS WITHOUT HETEROGENEITY

Explanatory Variable	DISEASE[1]				OUTCOMES		VISITS	
	DM	DNU_0	DNU_1	DNU_2	DEATH	AMPUTATION	GENERAL	PODIATRIST
EARLY DIAGNOSIS								
Time with undiagnosed DM		0.0197***	-0.0882	0.0037	0.0151***	0.6405		
		(0.0049)	(0.2614)	(0.0087)	(0.0047)	(0.5147)		
Time with undiagnosed DNU_0			-0.0111	0.0509*	0.0154	-0.0208		
			(0.0205)	(0.0297)	(0.0187)	(0.0236)		
Time with undiagnosed DNU_1				-0.0918***	-0.0498*	0.0074		
				(0.0289)	(0.0258)	(0.0250)		
Time with undiagnosed DNU_2					-0.0069	0.0683**		
					(0.0273)	(0.0273)		
One Year General Visit (6 month lag)		0.1024	-0.2307	0.4267	0.3901***	0.4530***		
		(0.1169)	(0.1880)	(0.2640)	(0.0761)	(0.1328)		
One Year Podiatrist Visit (6 month lag)				-0.1745	0.0327	-0.4019*		
				(0.1805)	(0.0954)	(0.2318)		
OTHER VARIABLES[2]								
Constant	-3.5167***	-3.9299***	-0.4078	0.0780	-8.2824***	-9.1748	0.3585***	-2.8954***
	(0.1166)	(0.2762)	(0.4294)	(0.5908)	(0.1642)	(0.4414)	(0.0258)	(0.0511)
White	-0.4287***	-0.0451	-0.1848	-0.0274	0.1137	0.1593	0.1039***	0.2229***
	(0.0621)	(0.0794)	(0.1243)	(0.1690)	(0.0758)	(0.1490)	(0.0141)	(0.0287)
Male	0.2879***	-0.0657	0.2327**	0.0264	0.2366***	0.6500	-0.2290***	-0.3283***
	(0.0406)	(0.0612)	(0.1016)	(0.1415)	(0.0505)	(0.0833)	(0.0095)	(0.0186)
High School or Better	-0.2324***	-0.0405	-0.1283	-0.0320	-1.1922***	-0.3027	-0.0318**	0.3683***
	(0.0596)	(0.0811)	(0.1274)	(0.1736)	(0.0905)	(0.1635)	(0.0129)	(0.0274)
Married	-0.1581***	-0.0042	-0.0584	0.1227	-0.0243	-0.5489	0.0381***	-0.2091***
	(0.0487)	(0.0696)	(0.1137)	(0.1610)	(0.0669)	(0.1324)	(0.0105)	(0.0203)
Time (in quarters)	-0.0577***	-0.0228	0.0263	-0.0541	0.1033***	0.0013	-0.0219***	0.0134***
	(0.0060)	(0.0156)	(0.0244)	(0.0335)	(0.0088)	(0.0311)	(0.0016)	(0.0026)
Time Square	0.0010***	0.0003	-0.0007*	0.0011*	-0.0010***	0.0002	0.0006***	-0.0001***
	(0.0001)	(0.0002)	(0.0004)	(0.0006)	(0.0001)	(0.0005)	(0.0000)	(0.0000)
Arthritis	0.3895***	0.0164	-0.1947	-0.0213	-0.0237	0.3689	0.5467***	0.4151***
	(0.0912)	(0.1244)	(0.1870)	(0.2262)	(0.1063)	(0.2784)	(0.0224)	(0.0322)
Year that a person becomes 65 (1991=0.1, 1992=0.2, …)	0.4581***	0.4248***	-1.0698***	-0.2297	-0.3541***	0.4112	0.3587***	-0.1811***
	(0.0786)	(0.1149)	(0.1767)	(0.2484)	(0.0949)	(0.1324)	(0.0165)	(0.0339)
EXCLUSION RESTRICTIONS								
Weighted average distance to general doctor							-0.2832***	
							(0.0355)	
Weighted average distance to podiatrist							-0.0402***	-0.3426***
							(0.0058)	(0.0140)
DURATION DEPENDENCE								
Contracted DM					0.6771***	-0.0547	0.5841***	-0.4809***
					(0.0776)	(0.1803)	(0.0119)	(0.0270)
Time with DM		-0.0128*	-0.0072	-0.0196	-0.0211***	-0.0050		0.0440***
		(0.0068)	(0.0100)	(0.0133)	(0.0058)	(0.0151)		(0.0009)
Time with DM Square		0.0074**	0.0126**	0.0103				
		(0.0035)	(0.0050)	(0.0065)				
Contracted DNU_0					1.0706***	-0.9616*	0.8414***	0.7622***
					(0.1532)	(0.4881)	(0.0421)	(0.0496)
Time with DNU_0			-0.4545***	-0.0501	-0.0362***	0.0305*		-0.0453***
			(0.0222)	(0.0316)	(0.0135)	(0.0177)		(0.0042)
Time with DNU_0 Square			0.4491***	0.0838				
			(0.0252)	(0.0511)				
Contracted DNU_1					-0.2534	2.7885***	-0.0755	1.1580***
					(0.2672)	(0.6153)	(0.0827)	(0.0829)
Time with DNU_1				-0.5516***	0.0467**	-0.0189		-0.0431***
				(0.0486)	(0.0196)	(0.0227)		(0.0076)
Time with DNU_1 Square				0.4274***				
				(0.0688)				
Contracted DNU_2					0.1367	2.6831***	0.3272***	0.0469
					(0.2722)	(0.3938)	(0.0827)	(0.0854)
Time with DNU_2					0.0141	-0.1628***		0.0602***
					(0.0194)	(0.0251)		(0.0073)
Log Likelihood	-231,522.278410							

***significant at 0.01 level ***significant at 0.05 level *significant at 0.1 level

1 Several Equations described in the text were estimated but are not reported. They include: two pre-age 65 hazards – DM and DNU0 ; two post-age 65-before first visit hazards – DM and DNU0 ; the transition to DM post-age 65-post first visit and the first doctor visit.

2 We also control for high school or better missing, marital status missing, and general visit continuity missing.