An empirical model of health care demand under non-linear pricing *

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Abstract

In 2004, the German Social Health Insurance introduced a co-payment for the first doctor visit in a calendar quarter. I combine a structural model of health care demand and a difference-in-differences strategy to estimate the effect of that reform on the number of visits. In the model, the implied incentive to delay a first visit also affects subsequent visits, as the expected remaining time to the end of quarter is reduced. This effect is overlooked in the prior literature using standard hurdle count models. Data are from the German Socio-Economic Panel. Results show no statistically significant reduction in visits due to the reform.

JEL Classification: C25, I10
Keywords: Count data, Poisson process, co-payment, hurdle model

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1 Introduction

Around 90% of the German population receive their health insurance coverage through the German statutory health insurance system (SHI). Before 2004, the SHI did not require any co-payment for doctor visits, although prescription drugs were subject to cost sharing for many years. Since January 1st, 2004, the insured had to pay a fee of 10 Euros for the first visit to a doctor in each calendar quarter. Additional visits in the same quarter were free of charge. Thus the individual out-of-pocket expense became a non-linear function of utilization, dropping from 10 to 0 Euros after the first doctor visit in a quarter. Only individuals without any visit to doctor during a quarter could avoid paying the fee.

A number of researchers have conducted quantitative evaluations of the effects of the 2004 reform on demand (Augurzky et al., 2006, Schreyögg and Grabka, 2010, Farbmacher and Winter, 2013). As in these papers, the focus of the present study will be on the number of individual doctor visits per quarter, as well as on the probability of no visits. Whereas the earlier literature relied on reduced form count data or binary response models to estimate the reform effect, I will analyse the effect in the context of a structural model of health care demand. It will be a very simple model based on a stochastic sickness arrival process and a random utility decision model for seeing a doctor. The non-linear pricing is represented by a change in the probability of a visit given that one is sick, and a corresponding shift in the hazard rate for visits.

Despite its simplicity, the model allows addressing some important dynamic aspects of the health care demand process that are absent in the other papers. For example, the co-payment for the first visit provides an incentive to delay, thereby reducing the expected fraction of a quarter during which visits have a price of zero. An extended version of the model also accounts for unobserved heterogeneity. A closed form probability function for the number of visits can be derived, and the model parameters are estimated by maximum likelihood. Some simple specification tests are available.

Regarding data and identification, this paper largely follows the lead of the prior literature. Data are from the German Socio-Economic Panel (SOEP, see Wagner et al., 2007). As in Augurzky et al. (2006), I use two years, 2003 as pre-reform period and 2005 as post-reform period. Data from 2004 are dropped, as most interviews take place during the first quarter of a year. For identification, a difference-in-differences strategy is used. The control group consisting of people with private health insurance provides a baseline, counterfactual trend in doctor visits pre-and post reform, for example due to changes in general economic conditions. Any deviation from this baseline trend observed for the treated group (SHI) is then assumed to reflect the effect of treatment.

Finally, I side with Farbmacher and Winter (2013) who worry about the discrepancy between calendar quarter (i.,e., pricing period) and reporting period. They introduce the notion of misclassification that arises if, unrecorded in the data and thus unobserved by the analyst, a visit has taken place between the start of the calendar quarter and that of the reporting period. In this case, the first visit in the reporting period has an effective price of zero under treatment, not of 10 Euros, as it would be the case, if the reporting period and the calendar quarter matched perfectly. Ignoring mismatch will tend to understate the true treatment effect. As a remedy, I follow Farbmacher and Winter (2013) and base my estimation sample on the subset of individuals that were interviewed at the end of a calendar quarter, or at least close to the end (within $\pm$ 10 days).

So far, substantive results have been mixed. Arguably, the introduction of a co-payment created an incentive to avoid doctor visits in a particular quarter of the year and one would expect the probability to visit a doctor within a quarter to decrease for those covered by by SHI relative to the privately insured. Augurzky et al. (2006) report a negative and statistically significant difference-in-differences coefficient in a logit model for “any visit”. In their preferred specification they control for individual specific fixed effects, and the coefficient switches sign and becomes insignificant. Schreyögg and Grabka (2010) estimate a hurdle-at-zero negative binomial model and find no effect in either part of the model. Farbmacher and

Winter (2013) find a statistically significant 4 percentage point reduction of the probability of any visit, for the non-misclassified observations. Here, I also avoid misclassification but nevertheless do not find a significant effect.

While the main contribution of the paper is the development of a new model of demand for doctor visits with non-linear pricing, and thus methodological, my results add to the existing evidence regarding the difficulty of obtaining robust estimates for the effect of the 2004 reform on health care utilization. Perhaps, household data from the SOEP provide simply too noisy indicators of utilization, and researchers should better turn their attention to insurance level data, as done for instance by Farbmacher et al. (2013).

2 Modeling the number of doctor visits

Suppose that sickness events arrive according to a Poisson process with rate λ. The total number of sickness events N during a quarter is then Poisson distributed with mean λ. At each event, the individual decides whether or not to see a doctor, by comparing two utilities, u_1 with a visit and u_0 without. Let utility be a function of income y net of the cost of a visit c. Then a visit takes place, and $X = 1$, if

$$u_1(y - c) > u_0(y)$$

and

$$\Pr(X = 1) = \Pr[u_1(y - c) > u_0(y)] = p(y, c)$$

With constant cost, the probability of a visit is the same for all sickness events, and the total number of visits

$$Y = X_1 + \ldots + X_N \tag{1}$$

has a compound Poisson distribution with mean $\lambda \times p(y,c)$ (Feller, 1977). Under the aforementioned reform, the cost of a visit is not constant, however, since, abstracting from opportunity cost, the first visit during a quarter has a price of c and only subsequent visits are free. Thus we have

$$\Pr(X_1 = 1) = p(y,c) > \Pr(X_j = 1) = p(y,0), \qquad j = 2, \ldots, N$$

Equivalently, the compound Poisson distribution (1) is given by the distribution of the number of "renewals" (i.e. completed time spells between visits) during a fixed time interval, if spells i.i.d exponentially distributed with rate $\lambda \times p(y,c)$. The non-linear pricing model is then characterized by a one-time jump in the hazard rate: $\lambda_0 = \lambda \times p(y,0)$ is the hazard rate for the time to first visit, and $\lambda_1 = \lambda \times p(y,c)$ that for the duration between subsequent visits. Under the assumptions of the model, $\lambda_0 < \lambda_1$. This "non-stationarity" violates the assumptions of a standard renewal process and leads to a new kind of count data model.

2.1 The distribution of the number of visits

Assume, as before, that sickness events follow a homogenous Poisson process. Hence, hazard rates are constant (non-time dependent) before and after the first visit. It follows that the time of the first visit t has an exponential distribution with rate λ_0, and the number of further visits during the quarter ocurring between t and T is Poisson distributed, $Y(t,T) \sim Poisson(\lambda_1(T-t))$. Moreover, for $k \geq 1$, the total number of visits during a quarter has probability

$$\Pr[Y(0,T) = k] = \int_0^T \frac{\exp(-\lambda_1(T-t))[\lambda_1(T-t)]^{k-1}}{(k-1)!} \lambda_0 \exp(-\lambda_0 t) dt \qquad .$$

One can show (see e.g. Baetschmann and Winkelmann, 2014) that the integral has closed form solution, and using the normalization $T = 1$ the probability function is given by

$$f(y;\lambda_0,\lambda_1) = \frac{\lambda_0 \lambda_1^{y-1} \exp(-\lambda_0)}{(\lambda_1-\lambda_0)^y}\left[1 - \sum_{j=0}^{y-1} \frac{\exp(-(\lambda_1-\lambda_0))(\lambda_1-\lambda_0)^j}{j!}\right] \qquad y = 1,2,\ldots \tag{2}$$

and $f(0;\lambda_0,\lambda_1) = \exp(-\lambda_0)$. If $\lambda_0 = \lambda_1$, (2) simplifies to the probability function of the Poisson distribution. The mean is given by

$$\mathrm{E}(y;\lambda_0,\lambda_1) = \lambda_1 + (1-\lambda_1/\lambda_0)[1-\exp(-\lambda_0)] \tag{3}$$

As required, the expected value of the distribution reduces to the Poisson mean when $\lambda_0 = \lambda_1$. The expected value is greater than λ_1 when $\lambda_0 > \lambda_1$, and smaller otherwise. A relative small value of λ_0 is an indication of "zero-inflation", or "extra-zeros", relative to the Poisson model, a situation encountered in many count data applications (Mullahy, 1986, Lambert, 1986).

2.2 Discussion

The non-linear pricing of the co-payment for the first visit introduces a one time jump in the hazard rate. The first visit is relatively costly, associated with a low hazard rate, whereas subsequent visits are free, increasing the probability that further (random) sickness events causes additional doctor visits.

The implied model for the first visit is identical to that used in a class of hurdle count data models introduced by Mullahy (1986). The probability function of the fixed hurdle is given by

$$\Pr(Y = k|x) = \begin{cases} p_0(\lambda_0) & \text{for } k = 0 \\ (1-p_0(\lambda_0))\dfrac{f(k|\lambda_1)}{1-f(0|\lambda_1)} & \text{for } k \geq 1 \end{cases}$$

where $f(k|\lambda_1)$ denotes the probability function of a standard count data model, i.e., Poisson or negative binomial distribution, and $p_0(\lambda_0)$ has a complementary log-log specification. Pohlmeier and Ulrich (1995) argue that such a hurdle model can be appropriate for modelling the demand for health care. In their interpretation, the first contact decision for a general practitioner often triggers a number of re-appointments or referrals to specialists that are subject to a different mechanism and thus a different λ.

The standard hurdle model, however, is not derived from an underlying stochastic process. It treats λ_0 and λ_1 as unrelated parameters that can be estimated separately. It ignores the random timing of the first visit, and thus the effect of λ_0 on the length of the period for which visits have a zero co-payment. Thus, it is not suitable to address the path dependence generated by non-linear pricing that I consider here. The "stochastic hurdle" in model (2) implicitly accounts for the timing of the first visit. The co-payment causes a lower stage 1 rate and decreases the expected time available for subsequent visits. Although the timing of the first visit, if any, is unobserved, the corresponding count data model can be derived under the maintained assumptions.

2.3 Identifying the effect of a co-payment on demand

In general, the two rates of the model can expressed as functions of a number of exogenous factors x, such as prior health status, income, gender, employment status and the like. Suppose that $\lambda_{i0} = \exp(x_i'\beta_0)$ and $\lambda_{i1} = \exp(x_i'\beta_1)$. The above model would suggest that with non-linear pricing, $\lambda_{i0} < \lambda_{i1}$, and thus

$$\exp(x_i'(\beta_0 - \beta_1)) < 1 \qquad \text{for all } i$$

However, attributing any such difference in rates to the existence of a co-payment for the first visit would require the absence of other explanations. But there are a number of factors that can rationalize a low initial rate and a higher one thereafter, perhaps the leading one being explored in the aforementioned paper by Pohlmeier and Ulrich (1995), where visits occur in clusters and a first visit is followed by additional appointments for a given sickness spell. Thus a different identification strategy is needed. In this paper, I adhere to the previous literature evaluating the 2004 reform and use difference-in-differences. Specifically, the co-payment was introduced in 2004 for those covered by SHI. Privately insured people were not affected and they can serve as control group. Consider the following model:

$$\lambda_{it,0} = \exp(\beta_{0,0} + \beta_{0,1}\, treat_i + \beta_{0,2}\, post_t + \beta_{0,3}\, treat_i \times post_t + x'_{it}\gamma_0)$$

where $treat_i$ is a dummy variable equal to one if the person is covered by SHI, and $post_t$ is a dummy variable equal to one in the post-reform year 2005. Thus, $treat_i \times post_t$ indicates active treatment, and $\beta_{0,3}$ is the treatment effect under the "parallel trends assumption". This assumption implies that the counterfactual 2005 hazard rate for a first visit for the SHI population in the absence of a co-payment is equal to the actual SHI rate before the reform in 2003 multiplied by a growth factor $\exp(\beta_{0,2})$.

In principle, one could specify the second hazard rate for further visits, $\lambda_{it,1}$ in a similar way. This offers a kind of placebo test, as, within the above model, the reform did not change the incentives conditional on a first visit, and no effect should therefore be observed (i.e., the null hypothesis $H_0 : \beta_{1,3} = 0$ should not be rejected).

2.4 Unobserved heterogeneity

The prior count data literature has emphasized the importance of unobserved heterogeneity in most applications. If such heterogeneity is ignored, any evidence of path dependence in the underlying stochastic process can be spurious. For instance, an excess of zeros does not need to indicate a differential hazard rate. It could equally well mean that the data are drawn from a mixture of two heterogeneous populations one of whom rarely or never goes to the doctor, while visits in the other group are generated from a Poisson process.

Unobserved heterogeneity can be introduced into the model semi-parametrically, or by using a specific distribution function. For the latter, suppose that $f(y_i|x_i, \epsilon_i)$ is Poisson distributed with rate $\exp(x_i'\beta + \epsilon_i)$ where $\exp(\epsilon_i) \equiv u_i > 0$ is i.i.d. gamma distributed with mean 1 and variance α. It is well known that the distribution of y_i conditional on x_i but unconditional on u_i is negative binomial with mean λ and variance $\lambda(1 + \lambda\alpha)$ (e.g., Cameron and Trivedi, 1986). Model (2) can be extended along the same lines. Let the two rates be given by $\lambda_j(x_i, u_i) = \exp(x_i'\beta_j)u_i$, $j = 0, 1$, where u_i is a gamma distributed individual heterogeneity term that equally affects both rates. The probability of observing a count y, conditional on x but unconditional on u is then given by

$$
\begin{aligned}
& f_{uoh}(y; \lambda_0, \lambda_1, \alpha) \\
&= \int_0^\infty f(y; \lambda_0 u, \lambda_1 u) g(u; \alpha) du \qquad (4) \\
&= \begin{cases} (\lambda_0/\alpha + 1)^{-\alpha} & \text{for y=0} \\ \dfrac{\lambda_0 \lambda_1^{y-1}}{(\lambda_1 - \lambda_0)^y} \left(\dfrac{\alpha}{\alpha + \lambda_0}\right)^\alpha \left[1 - \displaystyle\sum_{j=0}^{y-1} (1-\theta)^j \, \theta^\alpha \dfrac{\Gamma(\alpha + j)}{\Gamma(\alpha)\Gamma(j+1)}\right] & \text{for } y = 1, 2, 3, \ldots, \end{cases}
\end{aligned}
$$

where $\theta = (\alpha + \lambda_0)/(\alpha + \lambda_1)$ and $g(u; \alpha)$ is the gamma density function with mean 1 and variance $\sigma_u^2 = \alpha$. For $\lambda_1 > \lambda_0$, the term in squared brackets is equal to the complementary cumulative distribution function of the negative binomial distribution. The mean of the model with unobserved heterogeneity is given by

$$
\begin{aligned}
\mathrm{E}_{uoh}(y|\lambda_0, \lambda_1, \alpha) &= \int_0^\infty \lambda_1 u + (1 - \lambda_1 u/\lambda_0 u)\,(1 - \exp(-\lambda_0 u)) g(u; \alpha) du \\
&= \lambda_1 + (1 - \lambda_1/\lambda_0)(1 - f_{NB}(0; \lambda_0, \alpha))
\end{aligned}
$$

The mean function preserves the essential structure of the mean of the model without heterogeneity, and simplifies to it for $\alpha = 0$.

2.5 Estimation and testing

One can estimate β_0, β_1 and α by maximum likelihood (Stata code is available from the author upon request). In the application below, the data include (two) repeated observations for each person, one for the pre-reform year 2003 and one for the post-reform year 2005. Assuming random sampling is therefore unrealistic. As an alternative to the direct modelling of the intertemporal dependence, one can perform quasi-likelihood estimation on the pooled observations and adjust the standard errors for clustering at the individual level. As shown by Vuong (1989), the standard likelihood ratio statistics for nested, but misspecified models do not have the normal chi-squared distribution in this case, and one should therefore rather use a Wald test, for example for testing the hypothesis that $\lambda_0 = \lambda_1$.

In addition, there is a possibility for an informal specification test of the new model. Define the binary event "any visit yes/no". Under the assumption of the model, this event has a Bernoulli distribution with complementary log-log link and parameter λ_0. Thus, λ_0 is identified from a separate binary model and does not require estimation of the full model. A specification test can be based on a comparison of $\hat{\beta}_0$ in the full model with that of a simple binary model (i.e., the first stage of the standard hurdle model). If the two differ a lot, the specification of the structural demand model with non-linear pricing is likely wrong. Alternatively, one can use the contrast to compute a Hausman-type test statistic.

3 Data and Results

The sample is restricted to individuals between the age of 20 and 60. Table 1 shows selected summary statistics of the variables employed in the estimation, separately by year. The sample is about evenly split between the pre- and the post-treatment year. In 2003, the number of doctor visits had a mean of 2.12, and 37 percent of all persons in the sample did not visit a doctor during the previous quarter. In 2005, the mean was slightly lower (2.07) although the proportion of people without any visits declined to 34.7 percent. Note that these numbers lump together the treatment (about 83 percent of the sample) and control groups. The remaining variables are additional determinants of health care utilization: two demographic variables (age and its square as well as gender), three socio-economic variables (years of schooling, unemployment and log of disposable household income), and a disability indicator.

— — — Table 1 about here — — —

In terms of overall fit, the simple Poisson model is clearly inferior to the two-part generalizations that introduce different parameters for the utilization (yes/no) decision and for the intensity of use. When not allowing for unobserved heterogeneity, the stochastic hurdle model has a substantially higher quasi loglikelihood value than the fixed hurdle model (-7010.7 as compared to -7351.1). I mentioned before the possibility of a Hausman specification test. Comparing estimates from a Bernoulli model with complementary log-log link with those of the first visit hazard in the stochastic hurdle model, the resulting quadratic form takes a value of 121.0, indicating a statistically significant difference, i.e., rejection of the new model.

One reason for rejection might be neglected heterogeneity. Allowing for such unobserved heterogeneity reverses the ranking of the fixed and stochastic hurdle models, although the difference amounts only to about 2 log points. Importantly, it leads to a further substantial increase in quasi loglikelihood values, and the Wald test rejects the null-hypothesis of no unobserved heterogeneity. Unfortunately, a Hausman test is not available, because unobserved heterogeneity is not identified in the simple Bernoulli model (See Pohlmeier and Ulrich, 1995). In the following, I focus on the results of the model with unobserved heterogeneity when discussing parameter estimates of the stochastic hurdle model shown in Table 3.

— — — Table 2 about here — — —

Recall that λ_0 is the hazard rate for the time to a first visit. The probability of no visit (or utilization) is then equal to the survivor rate $\exp(-\lambda_0)$. Harzard rate and survivor rate are inversely related, i.e., factors increasing the hazard rate lower the probability of no visit, and vice versa. With the exponential parameterization, the displayed coefficients indicate the predicted approximate relative change in the hazard rate associated with a unit change in the associated regressor. The exact relative change is obtained from the transformation $\exp(\hat{\beta}_j) - 1$. For instance, the hazard rate for a first visit for men is $(\exp(-0.783) - 1) \times 100 = 54.3$ percent below that of women.

There are some interesting asymmetries between first-visit hazard (λ_0) and that of subsequent visits (λ_1). For instance, income has no effect on the former, but a statistically significant negative effect on the latter, where a 10 percent increase in income is predicted to reduce the hazard rate for each further doctor visit by 2 percent. A similar pattern holds for unemployment. Individuals with disabilities have higher hazard rates in both states, and thus a higher predicted number of doctor visits, than individuals without.

The point estimate of the treatment effect is a 20 percent reduction in the hazard rate for the first visit. However, it is measured imprecisely, and the hypothesis of no effect cannot be rejected at conventional levels of significance. The effect on the stage 2 hazard (were the model would predict none) is positive, but in magnitude only 1/3 that of the stage 1 hazard, and also statistically insignificant.

4 Concluding remarks

This paper introduced a simple model of health care demand under non-linear pricing, based on a Poisson process for the arrival of sickness events. In the model, introducing a co-payment for the first visit during a calendar quarter should lower the hazard rate for the first visit (stage 1 hazard), leaving the subsequent (stage 2) hazard for further visits unchanged. The model was applied to an evaluation of a German health care reform of 2004 when a co-payment of 10 Euros was introduced for those covered by statutory health insurance. In my preferred specification allowing for unobserved heterogeneity, and using a difference-in-differences setup, no statistically significant of the reform was found.

While the results thus confirm those of two earlier studies by Augurzky et al. (2006) and Schreyögg and Grabka (2010) who also found no effect of the reform on utilization, the new methodological approach of this paper offers a number of insights that might prove useful for future research in related contexts. For instance, the perspective of a stochastic process is useful to understand that any changes to the first hazard likely also affects the distribution of additional visits, simply because it changes the time left in the quarter to accumulate such visit. Thus, it is misleading to conclude that "the number of doctor visits of a person within a quarter should not be affected conditional on having visited a doctor at least once in the quarter" (Augurzky et al., 2006, p.4). Second, while not explored in this paper, the approach also points towards a theory consistent way to derive the likelihood of mismatched observations, i.e., observations for which reporting period and calendar quarter do not overlap. Implementing such an approach would avoid a loss of information incurred by limiting the sample to people interviewed at the end of a calendar quarter, and thus increase power.

Finally, there are also a number of obvious limitations resulting from the simple sickness arrival process and the rather mechanical decision process. For instance, a richer model might account for delay, whereby a sickness episode shortly before the end of a quarter leads to a visit just at the beginning of the next quarter, if no visit has taken place up to that point. There is also the possibility of anticipated visits, e.g. for health preservation rather than acute sickness, towards the end of a quarter where a visit has already taken place.

Furthermore, expectations may matter. As Farbmacher et al. (2013) point out, individuals who expect (or even know for sure) that they have to visit a doctor at least once during the payment period have little incentive to postpone their first visit, even if that visit is costly. Forward looking individuals should therefore have been unaffected by the 2004 reform, if their subjective probability of having to visit a doctor at least once was high, in contrast to those with a low subjective probability. Using a finite mixture model for the probability of any visit, Farbmacher et al. (2013) find indeed evidence in support for such heterogeneous effects. Standard evaluation approaches focussing on average effects might therefore yield misleading policy conclusions.

References

Augurzky, B., T.K. Bauer and S. Schaffner, S. (2006) Co-payments in the German health system - do they work? RWI Essen Discussion Paper No. 43.

Baetschmann, G., and R. Winkelmann (2014) A Dynamic Hurdle Model for Zero-Inflated Count Data, unpublished manuscript.

Cameron, A.C. and P.K. Trivedi (1986) Econometric models based on count data: comparisons and applications of some estimators and tests, *Journal of Applied Econometrics* 1: 29-53.

Farbmacher, H. and J. Winter (2013), Per-period co-payments and the demand for health care: evidence from survey and claims data, *Health Economics*, 22, 1111 - 1123.

Farbmacher, H., P. Ihle, I. Schubert, J. Winter and A.C. Wuppermann (2013) Heterogeneous Effects of a Nonlinear Price Schedule for Outpatient Care (No. 4499), CESifo Working Paper.

Feller, W. (1977), *An Introduction to Probability Theory and Its Applications*, second edition, New York: John Wiley & Sons.

Lambert, D. (1992) Zero-inflated Poisson regression with an application to defects in manufacturing, *Technometrics* 34: 1-14.

Mullahy, J. (1986), Specification and testing in some modified count data models, *Journal of Econometrics*, 33, 341-365.

Pohlmeier, W. and V. Ulrich (1995), An econometric model of the two-part decisionmaking process in the demand for health care, *Journal of Human Resources*, 30, 339-361.

Schreyögg, J., and M.M. Grabka (2010) Co-payments for ambulatory care in Germany: a natural experiment using a difference-in-difference approach, *European Journal of Health Economics*, 11(3), 331-341.

Vuong, Q.H. (1989), Likelihood ratio tests for model selection and non-nested hypotheses, *Econometrica*, 57, 307-333.

Wagner, G.G., J.R. Frick and J. Schupp (2007), The German Socio-Economic Panel Study (SOEP): scope, evolution and enhancements, *Schmollers Jahrbuch*, 127 , 139-169.

Table 1. *Means and standard errors by year*

	2003 (N=1649)		2005 (N=1745)	
	Mean	(Std. Err.)	Mean	(Std. Err.)
Number of doctor visits	2.120	(0.077)	2.072	(0.069)
Any visit (yes/no)	0.630	(0.011)	0.653	(0.011)
SHI (yes/no)	0.836	(0.009)	0.821	(0.009)
Age	40.24	(0.254)	41.20	(0.256)
Years of schooling	12.21	(0.066)	12.29	(0.064)
Unemployed (yes/no)	0.058	(0.005)	0.051	(0.005)
Disability (yes/no)	0.053	(0.005)	0.069	(0.006)
Male (yes/no)	0.482	(0.012)	0.482	(0.011)
Log net household income	10.47	(0.014)	10.52	(0.015)

Source: Socio-Economic Panel (SOEP), version 26, doi:10.5684/soep.v26

Table 2. *Model fit (N = 3394)*

	quasi loglikelihood	# of parameters
Poisson	-8181.4	11
Fixed hurdle, no unobserved heterogeneity	-7351.1	22
Stochastic hurdle, no unobserved heterogeneity	-7010.7	22
Negative binomial	-6446.8	12
Fixed hurdle, unobserved heterogeneity	-6417.4	23
Stochastic hurdle, unobserved heterogeneity	-6419.5	23

Table 3. *Stochastic hurdle models of health care utilization (N=3394*

	Poisson	Without heterogeneity		With heterogeneity	
	λ	λ_0	λ_1	λ_0	λ_1
Post	0.001	0.202**	-0.266	0.249	-0.139
	(0.114)	(0.100)	(0.202)	(0.212)	(0.147)
Treat	-0.197*	0.014	-0.379**	-0.117	-0.306**
	(0.101)	(0.085)	(0.181)	(0.175)	(0.130)
Post×Treat	-0.047	-0.162	0.151	-0.203	0.068
	(0.125)	(0.110)	(0.218)	(0.228)	(0.157)
Age	0.031*	-0.010	0.067**	0.006	0.050**
	(0.017)	(0.015)	(0.027)	(0.029)	(0.020)
Age squared$\times 10^{-2}$	-0.026	0.020	-0.071**	0.010	-0.050**
	(0.021)	(0.019)	(0.034)	(0.036)	(0.024)
Years of schooling	-0.008	0.001	-0.014	-0.002	-0.016
	(0.009)	(0.009)	(0.014)	(0.017)	(0.011)
Unemployment (yes/no)	0.366**	0.020	0.483**	0.106	0.437**
	(0.102)	(0.086)	(0.162)	(0.194)	(0.128)
Disability (yes/no)	0.787**	0.589**	0.545**	1.752**	0.688**
	(0.076)	(0.085)	(0.113)	(0.305)	(0.086)
Male (yes/no)	-0.411**	-0.386**	-0.213**	-0.783**	-0.315**
	(0.052)	(0.044)	(0.084)	(0.075)	(0.061)
Log net household income	-0.145**	0.006	-0.242**	-0.059	-0.187**
	(0.044)	(0.037)	(0.067)	(0.080)	(0.050)
σ_u^2					0.320**
					(0.055)

Source: Socio-Economic Panel (SOEP), version 26, doi:10.5684/soep.v26

Dependent variable: Number of doctor visits; Cluster robust standard errors in parentheses.