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How Did the German Health Care Reform of 1997 Change the Distribution of the Demand for Health Services?

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December 15, 2003

Abstract

I consider the problem of evaluating the effect of a health care reform on the demand for doctor visits when the effect is potentially different in different parts of the outcome distribution. Quantile regression is a useful technique for studying such heterogeneous treatment effects. Recent progree has been made to extend such methods to applications with a count dependent variable. An analysis of a 1997 health care reform in Germany shows the benefit of the approach: lower quantiles, such as the 25 percent quantile, fell by substantially larger amounts than what would have been predicted based on Poisson or negative binomial models.

JEL Classification: I11, I18, C25

Keywords: heterogeneous treatment effect, count data, quantile regression, Poisson model

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1 Introduction

Suppose we want to estimate the effect of a health care reform on individual behavior, such as an individual's demand for health services. In such circumstances, it makes a great difference whether we assume the effect to be the same for all individuals, or whether we allow it to be different across individuals. Heterogeneous treatment effects can arise in many different ways. Examples include random variation of the treatment effect in the population, possibly combined with non-random selection into treatment, and different treatment effects for subgroups of the population, where groups differ on observable characteristics (a model with an interactive structure).

Here, a different notion of heterogeneity is explored, namely one in which the effect of the reform is diffent in different parts of the distribution of the outcome of interest. To fix ideas, consider the demand for health services as measured by the number of doctor visits during the previous quarter, a count variable, and its change in response to a health care reform that increases the out-of-pocket expense for prescription drugs. In such a situation, it may be of substantive interest whether the policy response is relatively larger among low users or among high users. In this case, the policy effect differs depending on the realization of the *dependent* variable.

The two benchmark count data models are the Poisson and negative binomial regression models with log-linear conditional expectation function. In such models, expected demand is affected proportionally by the reform. However, a given proportional change in expected demand can be associated with quite different changes in the outcome distribution. In the one-parameter Poisson distribution, changes in the expected value are in on-to-one correspondance with changes in the probabilities. In the negative binomial model, an additional parameter relaxes this strict relation somewhat. Still, both models arguably are too restrictive to investigate the full distributional effect of the reform, i.e., to estimate the reform effect in different parts of the outcome distribution.

Given this problem, there are a couple of ways to proceed and analyse the data using more general models. The approach pursued in this paper is based on quantile regression methods for count data, applying a methodol recently developed by Machado and Santos Silva (2002). Basically, the approach transform the discrete data problem into a continuous data problem by adding a random uniform variable to each count. The quantile regression functions of the transformed variable can then be estimated using standard quantile regression software. To interpret the results, one can compare the freely estimated quantile functions to those implied by the respective Poisson or negative binomial estimates in order to detect excess sensitivity in specific parts of the distribution, such as the lower or upper tails.

This methodology is applied to an evaluation of a German health care reform of 1997, using data from the *German Socio-Economic Panel*. The main result is that the reform effect was relatively more pronounced in the left part of the distribution: lower quantiles, such as the 25 percent quantile, fell by substantially larger amounts than what would have been predicted based on Poisson or negative binomial models. This finding has important policy implications. It is compatible with the notion that the demand for more frequent users of health services, among them the chronically sick, is relatively inelastic.

2 The German Health Care Reform of 1997

More than 90 percent of the German population is covered by statutory health insurance. The insurance reimburses the cost of doctor visits (including visits to general practitioners, specialists, and dentists), hospital stays, and qualifying prescription drugs. Only physicians can issue such a prescription, so that a doctor consultation must in general precede the purchase of the drug. Prescription drugs are dispensed by retail pharmacies who charge the insurance companies for the uniform price of the prescription, minus a co-payment that is required of the patient. The amount of the co-payment varies by package size. It increased substantially on July 1, 1997, by a fixed amount of DM 6 relative to a year earlier. Since the absolute amount of the co-payment is a function of the package size, after the reform DM 9 for small, DM 11 for medium and DM 13 for large sizes, the relative effect of the 1997 reform was largest for small sizes, where it amounted to a 200 percent increase.

How large was the effect of the increased co-payment on the demand for prescription drugs and other aspects of health care utilization, and how successful was the reform in reducing perceived excess demand for health services? In assessing the effects of the reform on the demand for health services, one can usefully distinguish between a direct and an indirect effect. The direct effect is a movement up the demand curve for prescription drugs, i.e., a reduced number of drug purchases after the reform, as the increased co-payment directly increased the patient's out-of-pocket expenses for drug purchases. The indirect effect is a potential inward shift of the demand curve for doctor visits. Since prescriptions are issued by physicians, the demand for doctor visits and the demand for prescription drugs are close complements and one can expect a negative cross-price elasticity.

Due to limited data availability, two prior studies have focussed on the effect of the reform on the demand for doctor visits (Winkelmann 2004a, 2004b). In both cases, data from a German household survey, the *German Socio-Economic Panel* (GSOEP), were used to estimate the 1996-1998 demand change induced by the reform for the affected group of people. In Winkelmann (2004a) a simple pre-post-reform comparisons was performed whereas Winkelmann (2004b) included observations on a control group to identify the reform effect in a differences-in-differences framework. In that analysis, it was found that for the control group, the change in the demand for doctor visits before and after the reform was practically zero, vindicating the simpler estimation strategy based on pre-post comparisons. In either case, the conclusion was that the reform caused a reduction in the individual's expected number of doctor visits by approximately 10 percent.

3 Marginal Probability Effects in the Poisson Model

The starting point of this paper is the recognition that regression models based on a single parameter Poisson distribution imply very restrictive probability changes in response to a change in a regressor. The standard Poisson model has probability function

$$f(y;\lambda) = \frac{\exp(-\lambda)\lambda^y}{y!} \tag{1}$$

where

$$\lambda = \exp(x'\beta)$$

Therefore, the first derivative $\partial f(y;\lambda)/\partial x$ can be written as

$$\frac{\partial f(y;\lambda)}{\partial x_j} = \frac{\partial f(y;\lambda)}{\partial \lambda}\frac{\partial \lambda}{\partial x_j} = f(y;\lambda)(y-\lambda)\beta_j \tag{2}$$

It follows that

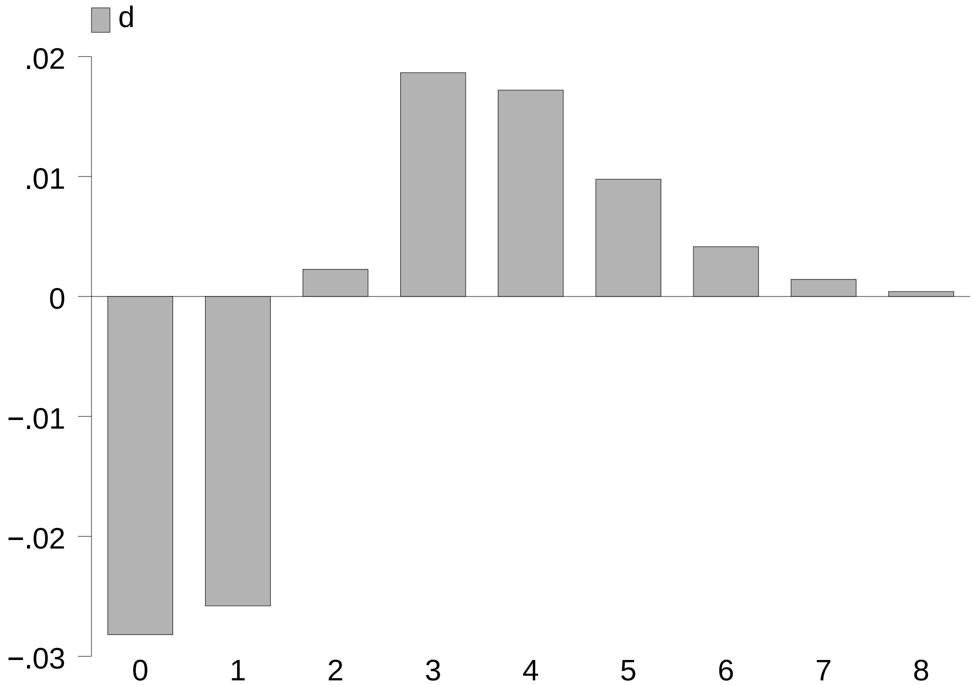
$$\text{sgn}(\partial f(y;\lambda)/\partial x_j) = -\text{sgn}(\beta_j) \text{ iff } y < \lambda$$

$$\text{sgn}(\partial f(y;\lambda)/\partial x_j) = \text{sgn}(\beta_j) \text{ iff } y > \lambda$$

The sign of the "marginal probability effects" is opposite the sign of β_j for all realizations below the mean, and of equal sign for all realizations above it. Figure 1 illustrates the situation. It is based on the conditional expectation function $\lambda = \exp(0.5 + 0.1 \times x)$ and shows the change in probabililities as x increases from one to two.

We notice the "single crossing" property of the marginal probability effects. Based on the Poisson probability distribution, only a single switch between positive and negative effects is possible. Also, the relative magnitudes of the effects are fully determined by functional form. We have to conclude that the Poisson model is not very well suited when the interest lies in modelling the full probability response to a change in a regressor. Note that this is *not* a problem of the particular conditional expectation function. One could choose the most general parameterization of λ possible, such as a generalized additive model, any arbitrary link function, or even a fully saturated model, the problem would not go away. All these approaches will translate into a specific response $\partial\lambda/\partial x$, which in turn will induce the very restrictive probability changes of the Poisson distribution (1).

Figure 1: *Example for Marginal Probability Effects in Poisson Regression Model*



The situation would also not improve if one were to chose the negative binomial model rather than the Poisson model as the basis for analysis. In fact, the sign rule and the single crossing property remain exactly the same as in the Poisson case. For example, for the Negbin II model (see e.g. Winkelmann, 2003) we obtain

$$\frac{\partial f_{NB}(y;\lambda,\xi)}{\partial x_j} = f_{NB}(y;\lambda,\xi)\left(\frac{\xi}{\xi+\lambda}\right)(y-\lambda)\beta_j \tag{3}$$

where

$$f_{NB}(y;\lambda,\xi) = \frac{\Gamma(\xi+y)}{\Gamma(\xi)\Gamma(y+1)}\left(\frac{\xi}{\xi+\lambda}\right)^{\xi}\left(\frac{\lambda}{\xi+\lambda}\right)^{y} \quad ,$$

ξ is a positive dispersion parameter, and λ is the conditional expectation as before.

To summarize, if one wants to model the probability response of a counted outcome more flexibly, and in particular allow for different responses in different parts of the distribution (relative to the benchmark Poisson or negative binomial models) one needs to turn to alternative modelling approaches. A first possibility is to abandon the rigid single index structure of the conventional approaches. The prime example is the hurdle model (Mullahy, 1986). In most applications, the hurdle is set at zero. In such models, the probability response of the zero outcome is entirely unrelated to the probability response in the strictly positive part of the distribution. Winkelmann (2004a) has applied such models in an evaluation of the effect of the aforementioned reform. He found that the response to the reform was significantly stronger in the left tail of the distribution (relative to the Poisson or negative binomial benchmarks) than elsewhere.

Here, I will analyse the same issue using a different approach that, rather than focussing on the probability function, concentrates on the dual problem of modelling the distribution function through quantile regression. This approach is developed in the next section.

4 An Analysis using Quantile Count Regression

The use of quantile regression for continuous random variables is by now quite standard. Since such regressions can be performed for arbitrary quantiles of a distribution, they provide a tool for modelling the effect of regressors on the full distribution of the outcome variable.

In the context of count data, the main problem is that the distibution function of a discrete random variable is not continuous. Hence, the quantiles are not continuous either, and they cannot be modelled directly as a continuous function of the regressors. However, this difficulty can be overcome, as shown by Machado and Santos Silva (2002). Let y be the count variable. The α-quantile of y is defined by

$$Q_y(\alpha) = \min(\eta | P(y \leq \eta) \geq \alpha)$$

where $0 \leq \alpha < 1$. The object of interest is the conditional quantile $Q_y(\alpha|x)$. Since $Q_y(\alpha|x)$ has the same support as y, it is discrete and cannot be a continuous function of x (such as $\exp(x'\beta)$). Therefore, Machado and Santos Silva suggest to introduce "jittering": consider a new variable z, obtained by adding a uniform random variable to the count variable

$$z = y + u, \qquad u \sim \text{ uniform } [0, 1)$$

where y and u are independent. Hence, z has density function

$$f(z) = \begin{cases} p_0 \text{ for } 0 \leq z < 1 \\ p_1 \text{ for } 1 \leq z < 2 \\ \text{and so forth} \end{cases}$$

(using notation $P(Y = k) = p_k$). Moreover, the distribution function of z can be written as

$$F(z) = \begin{cases} p_0 z \text{ for } 0 \leq z < 1 \\ p_0 + p_1(z-1) \text{ for } 1 \leq z < 2 \\ \text{and so forth} \end{cases}$$

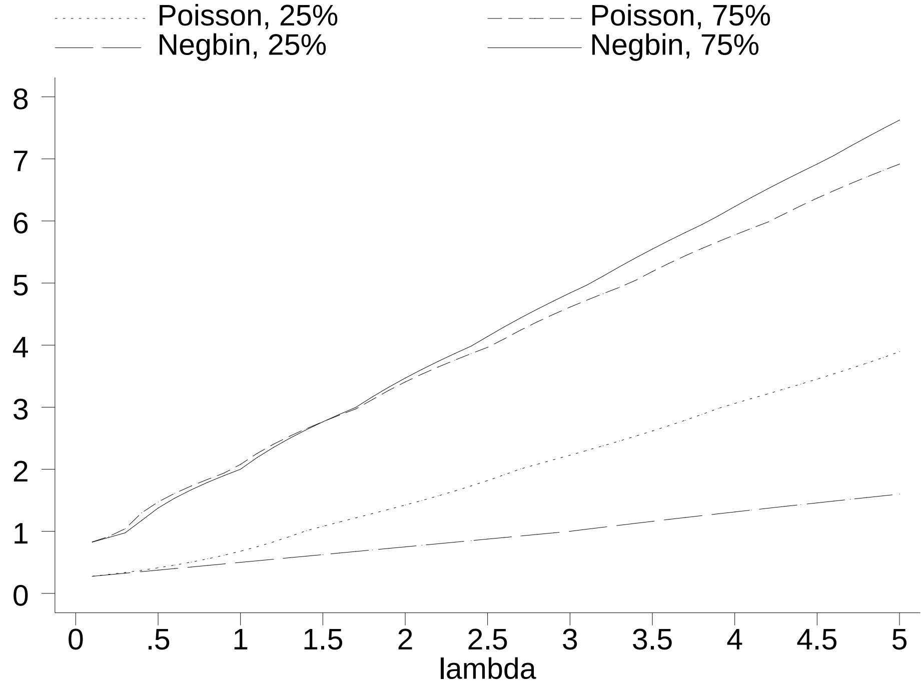
We see that the quantiles of z are continuous. For example,

$$Q_z(\alpha) = \frac{\alpha}{p_0} \text{ for } \alpha < p_0$$

$$Q_z(\alpha) = 1 + \frac{\alpha - p_0}{p_1} \text{ for } p_0 \leq \alpha < p_0 + p_1$$

These z_α quantiles can be easily computed and plotted as a function of the parameters if the underlying count variable has either a Poisson or a negative binomial distribution. In

Figure 2: *Quantiles of Poisson and Negative Binomial Distributions With Continuity Correction*



the Poisson case, $Q_z(\alpha)$ depends on λ only whereas in the negative binomial case, it depends on λ and ξ. Figure 2 displays the $z_{0.25}$ and the $z_{0.75}$ quantiles for the Poisson and negative binomial distribution as a function of λ (for $\xi = 1$).

Of course, the main advantage of this approach is that the quantiles can now be estimated freely, without imposing any more or less arbitrary and restrictive distributional form assumptions. Following Machado and Santos Silva (2002), let

$$Q_z(\alpha|x) = \alpha + \exp(x'\gamma(\alpha)), \quad \alpha \in (0, 1) \tag{4}$$

α is added on the right side in order to impose the lower bound of $Q_z(\alpha)$. Next, transform

z such that the transformed quantile function is linear:

$$Q_{T(z;\alpha)}(\alpha|x) = x'\gamma(\alpha)$$

where

$$T(z;\alpha) = \begin{cases} \log(z-\alpha) & \text{for} \quad z > \alpha \\ \log(\xi) & \text{for} \quad z \leq \alpha \end{cases} \tag{5}$$

and $0 < \xi < \alpha$.

The model suggest the following empirical implementation. First, one adds uniformly distributed pseudo random numbers to the observed counts. Second, one transforms the resulting data. Third and finally, the parameter estimates are obtained as solution to

$$\min \sum_{i=1}^{n} \rho_\alpha(T(z_i;\alpha) - x_i'\gamma)$$

where $\rho_\alpha(\nu) = \nu \times (\alpha - I(\nu < 0))$.

Machado and Santos Silva (2002) prove consistency and asymptotic normality of this estimator. Although the quantile function is not differentiable everywhere (the distribution function has corners), these points do not affect the derivation as long as there is at least one continuous regressor, because in this case these corner points have measure zero.

In order to interpret the results of the quantile regressions, I will first estimate standard Poisson and negative binomial regression models and predict selected quantiles (25 percent, 50 percent, 75 percent, 90 percent) before and after the reform, where all other variables are held constant at their mean values. From these predictions, the relative response of the various quantiles can be computed. This relative response is directly comparable to the semi-elasticities of the reform effect in the freely estimates quantile regressions. A comparison then shows whether the reform had unusual effects in selected parts of the distribution, relative to what would have been predicted on the basis of the Poisson and negative binomial benchmarks.

5 Data and Results

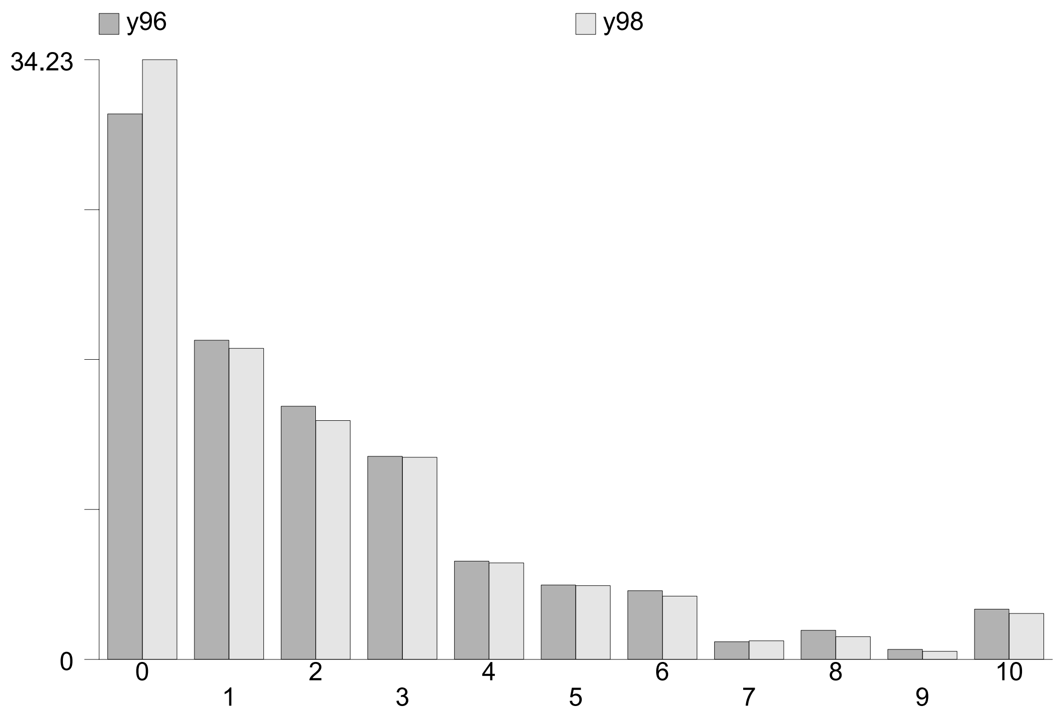
The GSOEP was initiated in 1984 (SOEP Group, 2001). It is an annual survey that is ongoing. For the purpose of this study, I selected a period of five years centered around the year of the reform, i.e., 1995 - 1999. The GSOEP has a handful of variables relating to the usage of health services. One of them is the number of visits to a doctor during the previous 3 months. I use observations on men and women from so-called Sample A, i.e., persons associated with non-guestworker-households in the original sample for West Germany. All individuals exempt from the reform (such youth and the privately insured) are excluded from the analysis. Deleting observations with missing values on any of the dependent or independent variables, the sample comprises 41375 observations.

The basic empirical strategy is to pool the data over the five years and estimate the effects of the reform by comparing the parameter of interest ($\hat{\lambda}$ in the case of the Poisson and negative binomial models, $\hat{Q}_z(\alpha)$ in the case of the quantile regressions) before and after the reform *ceteris paribus*, i.e., for an individual with constant characteristics. The effect is entirely captured in the year effects. For instance, let

$$\lambda_{it} = \exp(x_{it}'\beta + \delta_{95}D_{95} + \delta_{97}D_{97} + \delta_{98}D_{98} + \delta_{99}D_{99})$$

where the year effect D_{96} is omitted and x_{it} includes a constant and all other characteristics controlled for in the regression. These include a second order polynomial in age, three indicators for the quarter of the interview, three indicators of employment status (*full-time*, *part-time*, *unemployed*) plus the variables *years of education*, *married*, *logarithmic income*, *household size*, *active sport*, *good health*, *bad health*. Then the parameter δ_{98} captures the reform effect. To be precise, $[\exp(\delta_{98}) - 1] \times 100$ gives the ceteris paribus percentage change in the expected number of doctor visits before and after the reform. If it is negative, the demand for doctor visits fell after the imposition of the increased co-payments.

Figure 3: *Number of Doctor Visits 1996 and 1998: Marginal Relative Frequencies*



The marginal relative frequencies of the number of doctor visits in 1996 and 1998 are displayed in Figure 3. The biggest change occurred for the frequency of the outcome "zero visits" which increased by 3.1 percentage points and also turns out to be the modal outcome in both years. The relative frequencies of positive outcomes tended to decrease between 1996 and 1998. Whether this pattern can be explained by conventional count data models is a question that will be answered by the following analysis.

The Poisson and negative binomial estimates are displayed in the first two columns of Table 1. The remaining two columns show the quantile regression results for the third and the first quartiles. A comparison of the Poisson and negative binomial models confirms the superiority of the latter, as expected. The estimated dispersion parameter in the Negbin model is 0.988, with standard error 0.017. A likelihood ratio test leads to a clear rejection of the Poisson model as well. Note also that the regression coefficients do not differ much between the two models.

The estimated effects of the socio-economic variables are quite standard for this type of model (see e.g. Cameron and Trivedi, 1986). Men have fewer doctor visits than women; labor market participants have fewer visits than non-participants; the largest influence is observed for the two health status variables. People who report in the survey a poor current health are estimated to have about four times as many doctor visits ($\exp[0.819 - (-0.617)] = 4.2$) compared to those who see themselves in good health. Most importantly, in either model, the estimated reform effect is a 10 percent reduction (exact: $\exp(-0.102) - 1 = 0.097$) in the expected number of doctor visits, ceteris paribus.

This effect can be translated into corresponding quantile changes. For example, in the Poisson model, the predicted value of λ drops from $\hat{\lambda} = 2.43$ to $\hat{\lambda} = 2.19$ if all the other variables are kept constant at their sample means. Based on Figure 2, we find a relative change of the first quartile by -11 percent, from 1.76 to 1.56, and a change of the third quartile by -6.6 percent, from 3.89 to 3.64. In the Negbin model, the change in the predicted mean number of doctor visits is the same as in the Poisson model. Fixing the dispersion parameter at its estimated value of 0.988, the implied values for selected quantiles are as follows. The first quartile decreases from 0.85 to 0.79, by 6.8 percent. The third quartile decreases from 4.02 to 3.73, by 7.3 percent. As could be already seen in Figure 2, the larger variance of the Negbin model leads to quantile functions that are steeper than the Poisson quantiles for the higher quantiles, and flatter for the lower quartiles.

All this information is collected in Table 2, where additional results for the median and for the 9th decile are included as well. Most importantly, the table also includes the relative quantile changes from freely estimated log-linear quantile regressions, as explained in the previous section. These changes are practically identical to the estimated quantile regression coefficients in Table 1. For example, the pre-post reform change in the first quartile is a predicted minus 17 percent. The change in the third quartile is a 9.1 percent reduction.

The results are unequivocal. First, note that the Poisson quantiles are not a useful benchmark to compare the freely estimated quantiles with, since the data clearly display overdispersion. A comparison of the Negbin quantiles and the freely estimated quantiles reveals the following patterns: in the Negbin model, the reform effect (in absolute value) is an increasing function of α; the reform effect implicit in the freely estimated quantiles, on the other hand, is a decreasing function of α: the largest effect is recorded for the smallest quantile, here the 25 percent quantile. Hence, the quantile regression result show what an analysis based on conventional count data models would definitely miss, namely that the sensitivity of the demand for health services to the reform of 1997 was excessively high in the left part of the distribution. The demand for health services at the 25 percent quantile, representing individuals who are rare users, dropped by 17 percent, whereas the 90 percent quantile, representing individuals who are frequent users decreased by only 5.8 percent. In other words, the demand for more frequent users of health services, among them the chronically sick, reacted relatively inelastically.

6 Concluding remarks

The German health care reform of 1997 was associated with an average decline in the number of doctor visits by 10 percent. In this paper it was shown that a sole focus on averages misses an important part of the story. A more detailed analysis using a novel quantile regression method for count data confirmed that the reform effect was quite heterogenous indeed, defined here as being diffent in different parts of the distribution of the outcome of interest. Rare users responded much more to the increased co-payment than frequent users, in relative terms. This finding corroborates an earlier analysis based on generalized parametric count data models, such as hurdle Poisson, hurdle Negbin and finite mixture models (Winkelmann, 2004a). However, the present approach based on quantiles provides a more robust tool for detecting departures from the benchmark models. It has the great advantage that it does not require the estimation of an alternative parametric, and possibly misspecified, generalized count data model.

An interesting substantive result of this paper is that it helps reconciling the present findings from the *German Socio-Economic Panel* with those reported in an earlier study of the same reform by Lauterbach et al. (2000), using a different survey. In that earlier study, the estimated reduction in the average number of doctor visits was just 4.4 percent, falling short of the 10 percent found here. The likely explanation for this discrepancy is that Lauterbach et al. based their analysis on a survey of pharmacy customers. Clearly, this approach produces a heavily selected sample in which frequent users of health services are overrepresented. Hence, a relatively small response is to be expected. However, as has been demonstrated in this paper, such a pharmacy based survey is inappropriate to predict the effect of the reform on rare visitors and, by implication, on the population at large.

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Table 1: *Results for Poisson, Negbin and Quantile Regressions*

	Poisson	Negbin	75%Quantil	25%Quantil
Age/10	0.070*	0.010	-0.057*	-0.127*
	(0.034)	(0.033)	(0.029)	(0.049)
Age squared/1000	-0.061	0.003	0.067*	0.177**
	(0.034)	(0.034)	(0.029)	(0.051)
Male	-0.154**	-0.227**	-0.276**	-0.442**
	(0.022)	(0.020)	(0.016)	(0.027)
Years of schooling/10	-0.021	-0.015	0.005	0.252**
	(0.040)	(0.039)	(0.032)	(0.056)
Married	0.087**	0.118**	0.123**	0.215**
	(0.024)	(0.022)	(0.018)	(0.031)
Household Size	-0.046**	-0.051**	-0.053**	-0.061**
	(0.009)	(0.008)	(0.006)	(0.010)
Active sport	0.045*	0.068**	0.077**	0.198**
	(0.020)	(0.020)	(0.017)	(0.029)
Good health	-0.608**	-0.617**	-0.590**	-0.792**
	(0.019)	(0.019)	(0.017)	(0.029)
Bad health	0.809**	0.819**	0.863**	0.979**
	(0.020)	(0.021)	(0.022)	(0.037)
Logarithmic income	0.077**	0.087**	0.096**	0.199**
	(0.024)	(0.023)	(0.019)	(0.032)
Full-time employed	-0.254**	-0.251**	-0.250**	-0.411**
	(0.026)	(0.024)	(0.020)	(0.033)
Part-time employed	-0.235**	-0.238**	-0.251**	-0.341**
	(0.033)	(0.032)	(0.028)	(0.048)
Unemployed	-0.146**	-0.138**	-0.108**	-0.261**
	(0.034)	(0.033)	(0.033)	(0.055)
Year=1995	0.017	-0.002	-0.023	-0.075
	(0.021)	(0.020)	(0.023)	(0.039)
Year=1997	-0.037	-0.045*	-0.056*	-0.093*
	(0.020)	(0.019)	(0.023)	(0.039)
Year=1998	-0.102**	-0.102**	-0.092**	-0.168**
	(0.020)	(0.020)	(0.023)	(0.038)
Year=1999	-0.104**	-0.100**	-0.111**	-0.089*
	(0.021)	(0.020)	(0.023)	(0.039)
Log-likelihood	-113318.3	-84833.1		

Notes to Table 1:

Source: *German Socio-Economic Panel*, years 1995, 1996, 1998 and 1999. Dependent variable: Number of Doctor Visits during previous quarter. Model includes furthermore a constant and three indicator variable for the quarter of the interview (winter, spring, fall). Estimated dispersion parameter in Negbin model is $\hat{\xi} = 0.988(0.017)$. The results for the 50 percent and 90 percent quantiles are not displayed. Robust standard errors adjusted for heteroscedasticity and for pooling observations over years in parentheses. Coefficients with ** are significant at the 5 percent level. Coefficients with * are significant at the 10 percent level. N=41375

Table 2: *Effect of 1997 Health Care Reform at Various Quantiles (1996-98 Relative Change)*

	q25	q50	q75	q90
Poisson model	-0.110	-0.082	-0.066	-0.052
Negbin model	-0.068	-0.070	-0.073	-0.083
Quantile regression	-0.168	-0.160	-0.091	-0.058

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