Journal of Behavioral and Experimental Economics 72 (2018) 9–16

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Economics

journal homepage: www.elsevier.com/locate/jbee

On using interval response data in experimental economics☆

James McDonald, Olga Stoddard*, Daniel Walton

Brigham Young University. Department of Economics, 130 FOB, Provo UT 84602, USA

ARTICLE INFO

Keywords:
Discount rates
Interval dependent variable
Distributional misspecifications

ABSTRACT

Many empirical applications in the experimental economics literature involve interval response data. Various methods have been considered to treat this type of data. One approach assumes that the data correspond to the interval midpoint and then utilizes ordinary least squares to estimate the model. Another approach is to use maximum likelihood estimation, assuming that the underlying variable of interest is normally distributed. In the case of distributional misspecification, these estimation approaches can yield inconsistent estimators. In this paper, we explore a method that can help reduce the misspecification problem by assuming a distribution that can model a wide variety of distributional characteristics, including possible heteroskedasticity. The method is applied to the problem of estimating the impact of various explanatory factors associated with individual discount rates in a field experiment. Our analysis suggests that the underlying distribution of discount rates exhibits skewness, but not heteroskedasticity, In this example, the findings based on a normal distribution are generally robust across distributions.

1. Introduction

Many empirical applications in the experimental economics literature involve interval response data. Examples include commonly used measures of risk aversion (see Harrison and Rutstrom, 2008; Charness et al., 2013, for an overview), second-price Vickrey auctions with interval bidding possibilities (Banerjee and Shogren, 2014), estimation of willingness-to-pay (WTP; Dominitz and Manski, 1997; Hanley et al., 2009, 2013) , and individual discount rates (Coller and Williams, 1999; Harrison et al., 2002). The typical critique against tasks that elicit point estimates in these contexts is “the payoff dominance” problem first raised by Harrison (1992). The Becker–DeGroot–Marschak (BDM) procedure, in particular, is known to have weaker incentives around the optimum. In addition, data that rely on single-response methods, such as the BDM, to elicit risk preferences or WTP are significantly noisier (Harrison, 1986).

Various methods have been considered to treat this type of data. One approach assumes that the data correspond to the interval midpoint and then utilizes ordinary least squares to estimate the model. Another approach is to use maximum likelihood estimation, assuming that the distribution of the underlying variable of interest is of a particular form, such as the normal. While these methods are widely used in the literature, they can yield inconsistent estimators and thus misleading results in cases of distributional misspecification or in the presence of heteroskedasticity.

In this paper, we consider the implications of using an estimator, which is based on a flexible distribution that can accommodate a wide range of skewness and kurtosis, hence having the potential to reduce the impact of distributional misspecification. In particular, we use maximum likelihood estimation of an interval response regression model that corresponds to the skewed generalized *t* distribution (SGT) and the generalized beta of the second kind (GB2). The SGT can model a wide range of distributional characteristics for real-valued skewed and leptokurtic data and includes many important distributions, such as the normal, Laplace, generalized error distribution, and skewed variations of these distributions as special and limiting cases. The GB2 is a flexible distribution for positive valued outcomes. These two flexible distribution functions serve as alternatives to the normal distribution often employed in interval regressions.

We apply this method to the problem of estimating the effects of various possible explanatory factors on individual discount rates in a field experiment described in Harrison et al. (2002), hereafter referred to as HLW. In this experiment, the authors elicit individual discount rates from subjects and test whether these rates vary (1) across households and (2) over time. HLW find that discount rates vary significantly with respect to several sociodemographic variables but not over a one- to three-year time horizon. This finding provides an important contribution to our understanding of the nature of individual discount rates, given their essential role in intertemporal welfare analyses.

☆ The authors would like to express their appreciation to Bryan Chia for the outstanding research assistance.
* Corresponding author.
E-mail address: olga.stoddard@byu.edu (O. Stoddard).

https://doi.org/10.1016/j.socec.2017.10.003
Received 18 October 2016; Received in revised form 20 October 2017; Accepted 22 October 2017
2214-8043/

In this paper, we consider the implications of allowing for more general distributions in estimating the model. We observe that the underlying distribution of reported discount rates exhibits skewness, heteroskedasticity, or both. This is inconsistent with the assumption of normality and can impact parameter estimates. When applying more flexible distributions, which allow for a wide range of skewness and kurtosis values, such as SGT and GB2, we find that the nominal discount rates are significantly impacted by some sociodemographic factors. We compare and contrast our results with those obtained under the assumption of normality and find that the magnitudes and statistical significance of the coefficients are sensitive to the specification used, but they are generally consistent with the findings of HLW.

In particular, our results show that the GB2 family generally dominates the SGT as it provides a better fit with fewer parameters. Within the GB2 family, the 2-parameter and 3-parameter gamma (GA) and generalized gamma (GG) distributions are arguably the best choice, considering fit, parsimony, and easy interpretation. An added advantage of the GB2 family over SGT is that an assumption of “heteroscedasticity” (making σ a function of covariates) is unnecessary, considerably simplifying the interpretation of parameters. For both the GA and GG, we find support for the HLW conclusion that rates appear to be somewhat greater at a 6-month delay than for the longer delays, but constant across the longer delays. We also find that in addition to the discount rate that predictors found to be significant in HLW, our estimation of the GB2 model uncovers additional statistically significant covariates.

This paper contributes to a growing literature in experimental economics, which emphasizes various approaches to data analysis that are widely used by other research communities (Ashley et al., 2010; Frechette, 2012). While we discuss some well-known methods and their application to interval response data, we also highlight a new methodological framework and its advantages. We emphasize the important implications that the underlying theory has for econometric models and show how to check robustness of results to model specifications.

We focus this paper on the impact of accommodating diverse distributional characteristics of individual responses of monetary discount rates, rather than addressing the more complicated problem of joint estimation of the distribution and an underlying utility function as explored in Anderson et al. (2008). The methodological framework is outlined in Section 2. Section 3 provides an application of the methods to the problem of estimating individual discount rates, and Section 4 concludes.

2. Methodology

2.1. The model and likelihood function

The proposed model can be summarized as follows:

$$y_i^* = X_i\beta + \varepsilon_i \quad i = 1, 2, \ldots, n \tag{1}$$

where only the thresholds containing the latent variable y_i^* are observed, X_i is a $1xK$ vector of explanatory variables with a corresponding $Kx1$ coefficient vector β, and the ε_i are assumed to be independently and identically distributed random disturbances. The observed upper and lower thresholds of the latent variable y_i^* are denoted by U_i and L_i, respectively.

Stewart (1983) notes that inconsistent parameter estimates may result from using regular ordinary least squares (OLS), with the dependent variable being assigned to the value of the interval midpoint, and the open-ended groups being assigned values on an ad hoc basis. Stewart outlines different approaches to yield MLE (maximum likelihood estimation) under the assumption of normality and applies these methods to the problem of estimating an earnings equation. Stata's *intreg* command facilitates MLE of interval response data in the case of normally distributed errors and allows for the presence of heteroskedasticity.

We also apply a MLE approach to this estimation problem but allow for possibly non-normal distributions, which can accommodate skewness and kurtosis. We begin by noting that the conditional probability that y_i^* is in the interval (L_i, U_i) is given by

$$\Pr(L_i \le y_i^* \le U_i) = F(U_i; \beta, \theta|X_i) - F(L_i; \beta, \theta|X_i), \tag{2}$$

where F(.) denotes the cumulative conditional distribution of y_i^* and θ denotes a vector of distributional parameters. The corresponding log-likelihood function for interval regression models is given by

$$\ell(\beta, \theta) = \sum_i \ell n[F(U_i; \beta, \theta|X_i) - F(L_i; \beta, \theta|X_i)] \tag{3}$$

Interval regression programs allow not only for interval data but for censored data as well. For example, the Stata interval regression program, *intreg*, accommodates right censored ($(-\infty, U_i]$) and left censored ($[L_i, \infty)$) data by replacing the corresponding terms in (3) with $F(U_i; \beta, \theta|X_i)$ and $(1 - F(L_i;\beta, \theta|X_i))$, respectively.

Maximum likelihood estimation (MLE) will be used throughout this paper where Eq. (3) is maximized over the unknown parameters (β and θ).

2.2. Distributional assumptions

As noted in the introduction, the properties of the parameter estimates can be sensitive to the distributional assumptions. The most common implementation of the MLE approach to this type of data in the literature is based on the assumption of normally distributed errors. As mentioned earlier, Stata's interval regression command (*intreg*) assumes normally distributed errors and is a Tobit-like estimator for grouped data. However, these estimators can be inconsistent if the errors are not normally distributed or are associated with heteroskedasticity. Adaptive or semiparametric estimation of econometric models avoid specifying a particular probability density function but may be difficult to implement. Partially adaptive estimation relaxes the normality assumption by adopting a more flexible probability density function to approximate the actual error distribution. Caudill (2012) uses a mixture of normal distributions. Cook and McDonald (2013) use an inverse hyperbolic sine distribution to estimate censored regression models, finding that this specification improves estimator performance for the cases considered. We will use the skewed generalized *t* (SGT) and the generalized beta of the second kind (GB2), each of which allows a wide range of skewness and kurtosis. The SGT can model real-valued responses and includes the normal as a special case. The GB2 is a flexible model for applications in which the responses are positive, such as in the example considered in Section 3.

2.3. The skewed generalized t distribution

The SGT was introduced by Theodossiou (1998) and extends the generalized *t* (GT) (McDonald and Newey, 1988) and the skewed *t* (ST) (Hansen 1994) and allows for a wide range of skewness and kurtosis; for example, see Kerman and McDonald (2013). Other special cases of the SGT include the skewed generalized error distribution (SGED), skewed Laplace (SLaplace), generalized error distribution (GED), skewed normal (SNormal), *t*, skewed Cauchy (SCauchy), Laplace, Uniform, Normal, and Cauchy. The five-parameter SGT can be defined by the following density function:

$$SGT(y; \mu, \lambda, \sigma, p, q) = \frac{p}{2\sigma q^{1/p} B\left(\frac{1}{p}, q\right)\left(1 + \frac{|y-\mu|^p}{q\sigma^p(1 + \lambda sign(y-\mu))^p}\right)^{q+1/p}} \tag{4}$$

where $-\infty < y < \infty$ and $B(., .)$denotes the beta function.

The SGED is a limiting case of the SGT defined by