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ABSTRACT: Survey research studies make extensive use of rating scales to measure constructs of interest. The bounded nature of such scales presents econometric estimation challenges. Linear estimation methods (e.g. OLS) often produce predicted values that lie outside the rating scales, and fail to account for nonconstant effects of the predictors. Established nonlinear approaches such as logit and probit transformations attenuate many shortcomings of linear methods. However, these nonlinear approaches are challenged by corner solutions, for which they require ad hoc transformations. Censored and truncated regressions alter the composition of the sample, while Tobit methods rely on distributional assumptions that are frequently not reflected in survey data, especially when observations fall at one extreme of the scale owing to surveyor and respondent characteristics. The fractional response model (FRM) (Papke and Wooldridge 1996, 2008) overcomes many limitations of established linear and non-linear econometric solutions in the study of bounded data. In this study, we first review the econometric characteristics of the FRM and discuss its applicability to survey-based studies in accounting. Second, we present results from Monte Carlo simulations to highlight the advantages of using the FRM relative to conventional models. Finally, we use data from a hospital patient satisfaction survey, compare the estimation results from a traditional OLS method and the FRM, and conclude that the FRM provides an improved methodological approach to the study of bounded dependent variables.

Keywords: Fractional response model, bounded variables, simulation,

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I. INTRODUCTION

Accounting research often entails the use of data collected from survey instruments that utilize Likert-type scales. These data are naturally bounded by the structure of the response scale, which, in its traditional form, lists a finite number of options representing increasing degrees of agreement or disagreement with a proposed statement. In many cases, owing to the nature of the study and the characteristics of the survey instrument, a non-trivial number of responses occur at the boundaries of the scale. Econometric modeling of bounded dependent variables presents thorny challenges, especially for non-binary variables with a significant number of observations at the extremes. The fractional response model (FRM) developed by Papke and Wooldridge (1996, 2008) provides an effective approach to deal with the challenges posed by bounded dependent variables. The FRM overcomes many limitations of established linear and non-linear econometric solutions and is increasingly being employed in archival research in social sciences. In this paper we discuss the potential for application of the FRM to the study of bounded dependent variables that are commonly encountered in survey-based accounting research.

Bounded variables exhibit peculiar distributional properties; as a result, in most cases bounded dependent variables are not amenable to linear regression models. While linear models might offer reasonable estimations of partial effects for non-extreme values of the explanatory variables, they suffer from two significant shortcomings with respect to functional form specification and to predicting outcomes. First, linear models allow predicted values to lie outside the interval determined by the measurement scale. Second, linear models predict constant partial effects of unit changes in the explanatory variables, independent of the beginning value of the predictor. That is, linear models do not account for the possibility that variables that are naturally bounded between a minimum and a maximum are subject to floor and ceiling effects and display non-constant responses to changes in the predictors as they approach the bounds (Papke and Wooldridge 1996). Prior literature has addressed the inadequacies of linear estimation methods in predicting bounded responses and suggested alternative econometric solutions. These methods are commonly utilized in accounting research, and include applications of logit and probit models, discriminant analysis techniques, Tobit models, truncated regressions, and censored regressions (Noreen 1998; Maddala 1991; Wooldridge 2012; Wooldridge 2002).

Logit and probit models are widely used to study binary response variables. These solutions are used to model the probability that a certain event is observed. Because probabilities are naturally bounded between zero and one, logit and probit models prevent predicted values from falling outside of the natural range of the response variable, and capture the non-linearity of the distribution. Researchers often use logit and probit regressions to model the dichotomization of underlying continuous latent variables (e.g. $P(y>a)$, where a is often chose arbitrarily (Rogers and Van Buskirk 2009; Beatty et al. 2010). In survey-based studies, these models are useful to estimate the probability of affirmative answers to dichotomous "yes/no" questions. Log-odds transformations are also applied to dependent variables representing proportions or percentages (Sanders and Tuschke 2007). These solutions are, however, not devoid of limitations. First, they often rely on strong distributional assumptions for the error terms that may not be representative of the population of interest. Additionally, observations that are at the extremes (corner solutions) are not directly tractable and require ad-hoc transformations such as Berkson's minimum chi-square method (Maddala 1983). Alternatively, these extreme values are dropped from the sample. Both solutions induce distortions in the distribution of observations included in the sample, which may influence the interpretation of the estimated coefficients and reduce the validity of the inferences drawn from hypothesis testing. Finally, in some cases, the observations at the corners, where the functions underlying logit and probit models are not defined, might be of particular interest to answer the research question.

In addition to survey-based studies, there are other occasions when bounded response variables are encountered in accounting research. Some accounting settings involve bounded response variables that are discrete random variables, for example, bond ratings (Ashbaugh-Skaife et al. 2006), analyst recommendations (Bradshaw 2004), and audit going-concern opinions (Kaplan and Williams 2013). Others present features of continuous random variables. Examples include, among many others, the percentage of goodwill impairment (Beatty and Weber 2006), the asymmetric timeliness of the effect of good and bad news on earnings (Dietrich et al. 2007), capital structure (Petacchi 2015), portion of foreign earnings permanently reinvested (Hanlon and Heitzman 2010), and the fraction of options exercised in a period of time (Armstrong 2007). Continuous variables that are bounded in nature are generally addressed using Tobit models, censored regressions, or truncated models. These approaches, however, suffer from important limitations, especially where the distribution of the variable is bounded both above and below, and a material portion of the sample observations falls at one of the bounds. The FRM represents a viable solution to address many of the econometric limitations that are found in the nonlinear solutions currently utilized to model continuous bounded dependent variables.

The FRM is an extension of the general linear model (GLM) to a class of functional forms that circumvent most of the known issues of the traditional econometric models for bounded variables. The FRM accounts for the boundedness of the dependent variable from both above and below, predicts response values within the interval limits of the dependent variable and captures the nonlinearity of the data, thereby yielding a higher fit compared to linear estimation models. Furthermore, the FRM does not require special data transformations at the corners and permits a direct estimation of the conditional expectation of the dependent variable given the predictors. The estimation of the model's parameters is based on a quasi-maximum likelihood method (QMLE), which generates fully robust and relatively efficient estimates under general linear model conditions (Papke and Wooldridge 1996).

Although the FRM presents significant advantages in the estimation of models with continuous bounded variables, in this study we focus on settings where the distribution of bounded response variables includes a material number of corner observations. The FRM has been utilized sparingly in archival settings. Examples include Core et al. (2008), which studies the fraction of CEO compensation articles with a negative tone, Bechmann and Hjortshøj (2009), which uses the FRM in the context of disclosures of option-based compensation, and Amir et al. (2010), which studies auditor independence pre- and post- Sarbanes-Oxley. Li (2013) uses the FRM in a study that predicts the percentage of material contracts filed via Form 8-K during a 12-month period. Armstrong et al. (2014) use the FRM to model the appointment of independent directors during the CEO's tenure. Chen et al. (2015) employ the FRM to study the weight of customer satisfaction metrics associated with performance compensation contracts.

Survey studies in accounting employing finite response scales often estimate statistical models using least squares regressions (Voußem et al. 2016; Arnold and Artz 2015; Mahlendorf et al. 2014; Speklé and Verbeeten 2014), partial least squares ordered logistic regressions (King and Clarkson 2015), and Tobit regressions (Indjejikian and Matejka 2009). Survey research employs numerical rating scales where the numbers are implicitly associated with response alternatives (e.g. degree of agreement or disagreement) to proposed statements (Rosenthal and

Rosnow 2008). The items on the scale are often regarded as ordered responses. Discrete regression models such as ordered logit or ordered probit are generally recommended for the modeling of this kind of variables (Wooldridge 2002; Maddala 1983). In many cases, however, the response variable scale represents a discrete realization of an unobserved continuous variable (Winship and Mare 1984; Wooldridge 2002). Additionally, due to respondent or surveyor bias (Van der Stede et al. 2007), data collected via surveys sometimes present significant mass at one of the extremes of the response scale, exposing the discrete regression models to estimation problems similar to those encountered with bounded continuous variables. The FRM can overcome some of these problems that arise in survey research settings.

In the next section we provide a brief commentary on econometric solutions frequently used to model bounded response variables. In section 3 we summarize the properties of the FRM. Using Monte Carlo simulations, we identify conditions under which the FRM is advantageous compared to other established econometric solutions in the presence of bounded response variables. Next, we provide an overview of archival accounting studies that have used the FRM, and refer to recent survey accounting studies to propose examples of settings where the FRM could be beneficial. In section 5 we provide an empirical illustration of the key benefits of the FRM by estimating a model of patient satisfaction ratings in Japanese hospitals. The last section concludes.

II. ECONOMETRIC MODELS FOR BOUNDED DEPENDENT VARIABLES

Variables are *bounded* when they can only assume values limited by a minimum value (bounded *below*), or a maximum value (bounded *above*), or both. Bounded variables primarily arise in four research situations. First, variables could be *naturally bounded* when they can only take values within the interval across the entire population because of the nature of the phenomenon being studied. Examples of naturally bounded variables include proportions and probabilities, where the variable cannot take values outside of the interval [0, 1] or [0, 100 percent], and count variables measured by nonnegative integers, such as the number of females within a group of individuals. Second, the characteristics of the research design can give rise to bounded variables. This type of boundedness is found in categorical variables, like bond ratings (Wescott 1984) or survey based studies that measure variables using Likert-type scales (Van der Stede et al. 2007). Third, bounded variables arise when researchers restrict their analysis to a defined subset of the population, and assign pre-determined values to observations that fall outside the interval of interest (e.g. *top-coding* (Wooldridge 2012)). Finally, bounded variables can be a consequence of missing data beyond a certain limit, as in the case of survey respondents refusing to answer questions about sensitive topics, such as their personal income level.

Linear methods such as OLS are inappropriate to estimate models of bounded variables. OLS regressions provide an estimation of the expected value of the dependent variable, but the predicted values may be outside the natural interval (e.g. negative values for proportion variables, which are naturally bounded between zero and one). Further, partial effects estimated via OLS regressions are constant and independent of the value of the predictor. Although this feature is conducive to an easier interpretation of the estimation results, constant partial effects are incompatible with dependent variable boundedness, especially in cases where a significant number of observations is at the corners. Parameters estimated using non-linear least squares (NLS), two-limit Tobit, and beta distributions are generally inefficient because distributions of naturally bounded variables are likely to exhibit heteroskedasticity (Wooldridge 2002; Papke and Wooldridge 1996).

Prior literature has provided viable nonlinear econometric solutions that addressed the challenges presented by bounded response variables (Maddala 1991; Wooldridge 2002). These solutions, however, are often based on strong distributional assumptions. Moreover, they are simply not applicable to certain settings relevant for accounting researchers. In the next section, we provide a brief overview of the proposed solutions and highlight their main limitations.

Logit and Probit

Logit and probit regressions are among the most common econometric solutions utilized by accounting researchers when dealing with bounded response variables. The underlying phenomenon is usually measured by a binary indicator variable that takes the value of 1 if the event occurs, and 0 otherwise. Logit and probit models estimate the probability of the occurrence of the event. Accounting research has employed binary dependent variables in numerous situations – for example, prediction of inventory valuation choices such as LIFO versus FIFO (Lee and Hsieh 1985; Morse and Richardson 1983), or the determinants of auditors' decisions to issue going concern reports (Carcello and Neal 2000). Often times the "event" is derived from a dichotomization of a continuous variable where the "occurrence" is noted when the observed variable assumes a value greater than an arbitrary cutoff point (see, for example, Blouin et al. (2010)).

Ordinal logit and ordinal probit regressions are commonly employed in the analysis of survey data employing Likert-type scales. Examples include the investigation of the propensity of managers to alter their decisions to invest in positive NPV projects in order to influence earnings (Graham et al. 2005), self reported percentages of performance pay for physicians (Ittner et al. 2007), and the informativeness of accounting information for credit ratings (Christensen and Nikolaev 2012).

Probit and logit models rely on functional forms that are well defined for values of the dependent variable that are strictly between the bounds. Stone and Rasp (1991) argue that accounting studies often involve predictor variables that are skewed and collinear. Another problem that occurs with bounded dependent variables is that, while they may be continuous over the unit interval, a material number of observations might assume values at the bounds (corner solution responses). Logit and probit regressions cannot be directly utilized to predict values at the boundaries because the functional form at the core of these models is not defined for independent variables equal to zero and/or 1. Ad-hoc transformations, such as the log-odds ratio have often been applied to allow for tractability of the values at the extremes. In other cases, these observations have been dropped from the sample, thus exposing the research model to potential issues in terms of sample-selection bias. Loudermilk (2007) demonstrates the limitations of commonly used ad-hoc transformations in the context of a study about the determinants of firms' dividend policies. A variable of interest in her study is share repurchases as a fraction of total payouts. This is a variable bounded between zero percent and 100 percent that exhibits mass at both corners because a substantial fraction (20 percent in each corner in her sample) of dividend-paying companies have share repurchase payouts of zero percent or 100 percent in any given year. Loudermilk (2007) provides analytical and empirical evidence that applying the log-odds transformation to the large number of observations at the extreme points of the interval or ignoring these corner solution outcomes by dropping them from the sample could lead to misleading interpretations of the statistical results.

Corner Solution Models

Reasons for observing response variables "piling-up" at the bounds of the distribution can derive from characteristics of the research design, or from features inherent to the nature of the dependent variable. Examples of the former case include *censored* samples wherein observations of the dependent variable that fall outside a given range are assigned the same summary value, and *truncated* samples where the dependent variable observations lying outside of the selected interval of interest are dropped from the dataset. A frequently observed censored variable in accounting research is Cash Expected Tax Rate (*CASH ETR*), which is defined as cash taxes paid divided by pre-tax income minus special items (Dyreng et al. 2008). It is traditional in accounting research to censor this variable at zero (consistent with Dyreng et al. 2008), although a substantial number of observations fall outside the [0, 1] interval (e.g. 7.58 percent for one-year *CASH ETR* in Dyreng et al. 2008). Censoring introduces distortions into the predicted distribution of the dependent variable, conditional on the predictors.

In other cases, the nature of the variable determines the presence of corner solutions. For example, Denis and Xu (2013) study the effects of insider trading restrictions on the structure and level of executive pay. One of their dependent variables is the Equity Pay Ratio, defined as the fraction of total compensation that is comprised of equity-based incentive pay. The amount of equity incentives equals zero for over half of their sample. Booth and Deli (1996) study the number of external directorship positions held by CEOs, a variable showing a material presence of observations at zero. Bushman et al. (1996) report that over half of the observations of each of four main dependent variables in their study of the relationship between individual performance and CEO compensation assume zero values (Bushman et al. (1996), Table 2). The response variables in the aforementioned studies share the characteristic of being bounded at the lower end of the distribution, with a positive mass observed at the bound. Tobit regression, which take into account the non-linearity of the distribution and the positive probability of having observations at the bound, are well suited to model variables with such behavior. When the variables are bounded at both extremes and assume extreme values with positive probability at both bounds, they can be modeled with two-limit Tobit regressions – that is, a combination of two Tobit models, each taking into account the boundedness and mass at one of the extremes. Armstrong (2007) uses two-limit Tobit to model the fraction of available options that are exercised by executives in a certain period of time.

Although truncated and censored models may yield better fit to the empirical observations than corresponding linear regressions, they are exposed to a high risk of sample-selection bias, especially in the case of truncated regression, where the investigator chooses to ignore any observation that is outside of the desired range of the dependent variable (Maddala 1991). Additionally, Tobit regressions, used in the case of censored samples, are particularly sensitive to issues generated by heteroskedasticity, which cause inconsistency and invalidate usual test statistics (Arabmazar and Schmidt 1981).

In some cases, the observed distribution is determined by a combination of decisions regarding a certain behavior. For example, Beatty and Weber (2006), in a study of determinants of goodwill write-offs, model the response variable as a combination of the decision to perform a goodwill write-off and the decision about the percentage of goodwill to be written off. The authors utilize a two-part model, where a probit regression predicts the probability of impairment, while a censored regression predicts the write-off percentage. This approach, however, assumes independence between the "participation" decision (i.e. the decision to perform a goodwill write-off) and the "amount" decision (i.e. the percentage of goodwill written off). This assumption is not always supported by the phenomena studied in accounting research. The FRM provides an alternative approach to the study of variables bounded at both extremes where observations "pile-up" at one end of the distribution.

III. THE FRACTIONAL RESPONSE MODEL

The FRM was first developed in response to the call for an econometric approach capable of modeling empirical bounded dependent variables that exhibit piling-up at one of the two corners (Papke and Wooldridge 1996). The FRM provides several advantages: (a) it does not require any special transformation of the values observed at the bounds, (b) it accounts for the non-linearity in the data, (c) it is fully robust under generalized linear model assumptions, and (d) it allows for direct recovery of the regression function for the dependent variable given the set of predictors.

The basic assumption underlying the FRM can be summarized as:

$$E(y|\boldsymbol{x}) = G(\boldsymbol{x_i\beta})\ \forall i \tag{1}$$

where *G(.)* is a known function with $0 < G(z) < 1 \quad \forall z \in \mathbb{R}$, which satisfies the requirement that fitted values lie in the unit interval. Examples of non-linear functional forms used for *G* include the logistic function $G(x) \equiv \Lambda(z) \equiv \frac{\exp{(z)}}{1+\exp{(z)}}$ and $G(x) \equiv \Phi(z)$, where $\Phi(.)$ is the standard normal cdf.[1] These functional forms do not depend on the sample size. The nonlinear estimation of the parameters of the model is performed via maximization of the Bernoulli log-likelihood function

$$l_i(\mathrm{b}) \equiv y_i \log[G(\boldsymbol{x}_i\mathbf{b})] + (1 - y_i)\log[1 - G(\boldsymbol{x_i}\mathbf{b})] \tag{2}$$

which is well defined for *0<G(.)<1*. The quasi-maximum likelihood estimator (QMLE)[2] of β is consistent and asymptotically normal, regardless of the distribution of the dependent variable, conditional on the predictors. That is, y_i could be a continuous variable, discrete variable or have

[1] A key difference between the FRM and the logit (or probit) regressions is that the FRM estimates the conditional expected value of the response variable, while logit and probit models predict the probability of occurrence of a certain event, which could require arbitrary dichotomizations of the dependent variable.

[2] The quasi-maximum likelihood estimation (QMLE) method allows for the possibility that the normal probability model might be misspecified (Greene 1951).

both continuous and discrete characteristics. This flexibility contributes to the wide applicability of the FRM model to a variety of research settings.

In order to represent a viable and advantageous alternative to the current econometric solutions used in presence of bounded data, the FRM needs to meet the following requirements. First, it must ensure that the values predicted for the dependent variable are within the unit interval, but allow for values at the extremes without ad-hoc transformations. Second, the estimators must be relatively consistent and the statistical tests for significance must be reliable. Third, it must be computationally simple. Finally, the FRM must provide a better fit, both in terms of variance explanation and functional specification, than linear probability models. Papke and Wooldridge (1996) satisfy these requirements by choosing a specific class of functional forms and employing Bernoulli quasi-likelihood estimation methods.

In an early application of the FRM, Papke and Wooldridge (1996) study the relation between employees' participation to 401K plans and the match rate offered by the company. The expectation about the shape of this relation is a non-linear functional form, with diminishing returns observed as the match rate offered by the company increases. The dependent variable (participation rate) is continuous and varies from 0 to 100 percent, with 40 percent of the observations lying at the upper bound of the interval.

The authors first perform an estimation using OLS and then compare the results with a model estimated using logit QMLE methods. The results show high statistical significance for the match rate variable and diminishing partial effects as the match rate increases. Additionally the model is appropriately specified based on the results of the RESET test, and the R^2 results are higher than that of the linear model. It is worth noting that the QMLE approach does not involve any maximization of R^2 for the estimation of $\hat{\beta}$. The comparison of a QMLE procedure with a linear estimation involving quadratic terms for the independent variables provides additional support to the superior fit of the FRM compared to linear models. Finally, the quasi-likelihood results are fully robust and relatively efficient under GLM assumptions.

One of the criticisms raised by the research community about the original formulation of the FRM relates to its apparent inadequacy to control for unobserved heterogeneity, which is a particularly salient concern when analyzing panel data. To correct for this potential shortcoming, Wagner (2003), in his application of the FRM to a study of the determinants of export trends among German firms, includes firm-specific intercepts in the logit formulation of the FRM to control for firm fixed effects. This approach is considered to be appropriate when one observes the entire population, as in Wagner's case. However, in the presence of random sampling or unbalanced panels, this approach may introduce an incidental parameter problem[3], especially when the panel comprises of a small number of periods and a large number of cross sectional observations (Papke and Wooldridge 2008). In response to the criticism about the adequacy of the FRM to capture firms fixed effects, Papke and Wooldridge (2008) extend their model to the analysis of panel data. In a study of the relation between school spending and students' performance in standardized tests they use a probit formulation of the FRM to allow for unobserved, time-invariant characteristics of the school districts, which may be correlated with district spending on education. The characteristics of the normal distribution underlying the probit formulation provide important modeling benefits, including computationally simple estimates of the model, allowing for unobserved exogenous explanatory variables and for endogenous spending choices by the districts.

[3]When nonlinear panel data models contain *n* dummy variable coefficients, such as firm ID's, the number of parameters increases with the number of firms in the sample. Consequently, the estimator of β is biased and inconsistent in presence of small numbers of periods (Greene 1951).

FRM and Average Partial Effects

Another critical issue related to non-linear econometric models is the difficulty in the interpretation of the coefficients. With linear models, the estimated coefficients provide information about both the sign and the magnitude of the predictor's effect on the dependent variable. These effects do not depend on the observed starting level of the predictor. In non-linear models, while the estimation results are immediately informative about the sign and statistical significance of the relation, the magnitude of the change in the dependent variable caused by a unit change in the predictor varies with the starting level of the latter. Point-partial effects are easily calculated in nonlinear models, but not the average effects across the population. The computation of average partial effects (APE) is instrumental to the interpretation of the economic magnitude of the relations of interest.[4]

The procedure for the estimation of APE within the FRM is particularly appealing due to the fact that its identification requires no assumptions in terms of serial dependence in the response variable, which may or may not be present in panel data analysis (Papke and Wooldridge 2008). The procedure involves calculating the marginal effect at every observation for the predictor variable, and then averaging the marginal effects across the range of the predictors (Greene 1951, p. 690). The interpretation of APE's is similar to that of linear regression coefficients. By calculating and interpreting APE's, the researcher obtains useful information about the average magnitude of the causal relation, without compromising the non-

[4] There are two ways in which the researcher can compute and interpret marginal effects similarly to the linear model. The first involves the evaluation of the slope of the relation at the mean value of the predictor (partial effects at the average – PEA, see Wooldridge (2002) p.575). The second requires the calculation of the marginal effect at every observation and, subsequently, the computation of the sample average of the individual marginal effects. The latter approach produces the average partial effects (APE). In large samples the two procedures would produce similar results. In the case in small samples, current practice favors the calculation of average partial effects (Greene 1951).

linearity of the model and its enhanced fit characteristics compared to the linear ones. In general, the comparison of the APE calculated for the FRM model and the linear regression coefficients portray a consistent story. The similarity of the average economic significance estimated by the two models might lead to the erroneous conclusion that a linear model could be sufficient for the estimation of partial effects. The distinction between partial effects and average partial effects however, is nontrivial. The FRM model allows to capture the nonlinearity of the relation and to obtain estimates of partial effects at different percentiles of the predictor distribution, accounting for nonconstant returns and yielding a better fit than the linear model. This ability of the FRM to tease out the differential returns, especially at the extreme values of the distribution of the dependent variable is particularly valuable to accounting research where the extreme values are meaningful from a theoretical as well as practical perspective.

In the following section we report the results from a simulation to provide a quantitative assessment of the FRM technique *vis-à-vis* other modeling techniques in the analysis of data using bounded dependent variables.

Simulation Results

We use Monte Carlo simulations to highlight conditions under which the FRM is particularly advantageous over other known models. We define a response variable $y^* = \alpha + f(x) + u$, where u represents unobserved heterogeneity assumed to be normally distributed, and x is a predictor, which is randomly obtained from selected probability distributions. The relation between x and y^* is defined by the function f, which can be linear or nonlinear. We then artificially bound the observations for y^* by substituting negative values with zero, and values greater than one with one. The resulting bounded variable (y) is our response variable of interest. We manipulate the probability distribution of x and the relation f. We then estimate the model $y = g(x)$ using OLS, Tobit regression, and the FRM. We draw the explanatory variable from one of three probability distributions: normal, beta, or Poisson. Normal and beta distributions describe the behavior of continuous variables, which could have different level of skewness. The Poisson distribution describes a discrete variable. To capture different types of nonlinearity in the population distribution, linear, quadratic, exponential and logarithmic functional forms are used to represent the relation between predictor and response variable, as indicated in Table 1. By construction, the dependent variable observations include a material number of boundary values. The Monte Carlo simulation performs 200 iterations. In each repetition, a sample of 1,000 observations is drawn from the selected probability distribution and estimated using OLS, Tobit and FRM. Regression coefficients and R^2 are averaged across the 200 repetitions for each estimation method and reported in Table 1. Additionally, we tabulate the estimates of the average partial effects (APE) at various percentiles of the distribution of the heterogeneity.

--- Insert Table 1 here ---

The results reported in Table 1 indicate that, while established linear approximations perform adequately for the estimation of the *average* partial effects, they do not capture the *nonlinearities* in the data. The last five columns in Table 1 report APEs at the 1st, 5th, 50th, 95th and 99th percentiles of the distribution of the predictor, which indicate nonconstant returns in majority of the cases. This information is not directly available when estimating the relations using linear approximations. To elaborate, consider a normal distribution of x, which has 0.166 mass at the corners. OLS indicates that the estimated β value is 0.834, which is not substantially different from the APE of 0.835 produced by the FRM. However, this is the *average* effect size – the FRM indicates that this average effect size is not obtained at the corners of the distribution.

For example, the effect size for observations at the 5th percentile of the distribution is 0.652. For observations at the 99th percentile of the distribution, the effect size is 0.473. Suppose the dependent variable of interest is percentage of goodwill written off consequent to the adoption of SFAS 142, and about half of the firms have a zero value (as in Beatty and Weber 2006). OLS, Tobit, or censored regressions have the potential to lead to flawed conclusions about the effect of predictors of the decision to take a goodwill write-off when SFAS 142 is adopted for observations at the boundaries of the distribution if the effect sizes vary at the boundaries as indicated in Table 1.[5]

Indeed, Table 1 indicates that effect sizes can be vastly different at the boundaries versus the middle of the distribution – for example if the mass at the corners is 0.317, then the effect size for a firm that is in the first percentile is almost 10 *times* lower than the effect size for a firm that is at the 50th percentile (0.189 versus 1.987 in Table 1, row 2). Additionally, the FRM reveals that the shape of the response function could be curvilinear, with larger effect sizes at the center of the distribution and lower effect sizes at the corners. To the extent that there is substantial mass at the corners, other estimation techniques that provide average effects would *overestimate* the effect size for the nontrivial number of firms that lie at the boundaries. Examination of the beta distribution with 0.220 mass at the corners reveals that the effect sizes are larger for observations at the 5th percentile than they are at the 50th, 90th, or 99th percentile. A Poisson distribution with 0.353 mass at the corner has an asymmetric curvilinear response with the effect size at the 99th percentile close to zero.

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[5]Beatty and Weber (2006) examine the determinants of goodwill write offs using a censored regression. They acknowledge the problem that arises because the percentage of goodwill cannot be below zero or above 100% (naturally bounded variable). However, the results from their censored regression model provide only the average effects and do not permit the estimation of different effect sizes at the corners of the distribution of the fractional dependent variable.

The results in Table 1 also indicate that while in general the FRM yields at least as good a fit as the OLS and Tobit, in the majority of the simulated conditions, the R^2 associated with the FRM is higher than in the other methods. In summary, the simulation results indicate that, compared to established linear econometric models, the FRM provides (a) additional information on the effect sizes at the corners versus the middle of the distribution, (b) information about the *shape* of the relation between explanatory and response variables, and (c) improved fit.

Applications of FRM to Research in Social Sciences

The FRM has been successfully utilized in research studies in economics and finance. An example is Czarnitzki and Kraft (2004), who investigate the influence of the degree of separation between ownership and management on firm innovativeness. They measure innovativeness as the share of sales generated by new product introductions. The magnitude of the investment in innovation results from the combination of two separate decisions. First the firm decides whether to invest in R&D or not. Second, the investment amount is determined. The authors discuss their choice of using the FRM instead of a more traditional approach based on a Tobit model. The Tobit approach would incorporate both decisions in one model, and the estimated coefficients would represent the effect of the predictors on the combination of the two decisions. The FRM, on the other hand, allows the authors to estimate the weights of the decision predictors separately for each decision, while treating the share outcome as a continuous variable bounded between zero and 100 percent. The general inference deriving from the application of the FRM is directionally consistent with the Tobit results, but the FRM provides additional benefits in the interpretation of the results.

Another example of FRM application is provided by Ramalho et al. (2011), who apply a two-part fractional response model to study the determinants of decisions related to capital structure. In their study, the decision of whether to issue debt is modeled using a binary variable. They apply the FRM to model the dependent variable, which is the amount of debt issued as a percentage of total assets. Bastos (2010) uses the fractional response approach to predict bank loans credit losses (i.e. the percentage of credit exposure that would become a loss if the borrower defaults). Loudermilk (2007) and Alli et al. (1993) apply the FRM to studies of dividend payout policies.

Examples of research in international economics include Wagner (2003), who combines firm fixed effects with FRM to analyze panel data. His study provides statistical evidence that overturns the results in extant studies of a positive concave relation between manufacturing firm size and export/sales ratio. Eickelpasch and Vogel (2011) study the determinants of export trends in the service industry and find that, when controlling for firm fixed effects, variables such as human capital and productivity have no significant effect on the firm's export behavior, while size and product diversification are still significant.

FRM Applications to Accounting Research

Bounded dependent variables are common in accounting research. In many cases, accounting researchers deal with naturally bounded variables that display a positive mass of corner responses. A brief review of the studies that have been published in the last few years in major accounting academic journals reveals that in the presence of bounded dependent models, research has typically applied a variety of estimation techniques such as linear estimation methods (OLS and LPM), logit and probit regressions, as well as Tobit or truncated regression models (Skantz 2012; Ittner et al. 2007; Ittner et al. 2003; Denis and Xu 2013; Jayaraman and Milbourn 2012; Bushman et al. 2004; Huddart and Lang 1996; Chen et al. 2013). Tax research involving bounded response variables with a "fat tail" includes studies by Blouin et al. (2010), Armstrong et al. (2012); Dyreng et al. (2014); Dyreng et al. (2010); Omer et al. (2012); Rego (2003). Studies of goodwill impairment include the aforementioned study by Beatty and Weber (2006), as well as Gu and Lev (2011). We do not provide an exhaustive list of papers that use bounded dependent variables. Rather, our goal is to emphasize the prevalence of such variables in accounting research.

The choice of an appropriate estimation method for the model describing the relation between predictors and response variables is crucial for the interpretation of the statistical results and the consequent inferential reasoning. Accounting research has started employing the FRM to study bounded response variables. For example, Core et al. (2008) examine the role of press coverage in monitoring and influencing executive compensation practices. They use the FRM because their dependent variable, which is defined as the fraction of CEO compensation articles with a negative tone to the total number of articles about CEO compensation, has a fat left tail (Table 3, page 10 of their study reports that median value of the response variable is zero). In their study of disclosures of option-based compensation, Bechmann and Hjortshøj (2009) use the FRM to predict the difference between the expected exercise date and the earliest possible exercise date divided by the entire exercise period in years. Amir et al. (2010) use the FRM in their study of auditor independence and the cost of capital before and after Sarbanes–Oxley because their measure of auditor independence is the ratio of audit fees to total audit plus non-audit fees, which could have mass at the right tail. Li (2013) uses the FRM in his study of the determinants of accelerated filing of material contracts. His primary dependent variable, which is the percentage of material contracts filed via Form 8-K during a 12-month period has a fat left tail. Armstrong et al. (2014) study the role of independent directors in firm transparency and use the FRM to estimate a model predicting the proportion of firms' independent directors who were appointed during the CEO's tenure. Chen et al. (2015) examine the effect of competition intensity and competition type on the use of customer satisfaction measures in executives' annual bonus contracts. One of their analyses uses the FRM to estimate the effect of potential drivers of the percentage of total compensation weight placed on customer satisfaction measures.

The FRM has potential to be used in survey research in accounting. In the next section we propose a brief overview of recently published survey-based accounting studies as examples of settings in which the FRM might be advantageous.

Survey Research

Surveys are commonly used in accounting studies and involve respondents' self-reporting of variables measured on a predetermined value range (Likert scale). A perusal of survey-based studies published in some of the leading accounting journals highlighted a number of studies exemplifying settings in which the FRM could be employed.[6] An example is Maas and Matejka (2009) who study the influence of the degree of functional responsibility of business unit controllers on role ambiguity and tolerance for data misreporting. The descriptive statistics of all the dependent variables collected via the survey display significant mass of corner responses. Indjejikian and Matejka (2009) use survey data to examine the relative propensity of using financial versus nonfinancial performance measures, as well as the reliance on unit level versus higher organizational levels metrics, to evaluate CFO performance. The study uses respondents' self-reported percentages of individual compensation packages related to financial, nonfinancial and subjective performance measures, as well as the degree of accounting and operating decentralization. All dependent variables reported in the study present observations at the

[6] Our goal is not to provide an exhaustive list of survey-based studies that would be amenable to the application of the FRM, but to offer some meaningful examples of suitable settings. All the studies cited in this section share the characteristic of studying response variables that are bounded and exhibit a single "fat tail" (i.e. positive probability mass at one of the bounds).

extremes (see Indjejikian and Matejka (2009), Table 2). Table 4 (page 1080) of their study reports the coefficients of the statistical model estimated using Tobit regressions. As delineated previously, Tobit regressions are suitable for settings in which the dependent variable is bounded at one of the extremes, presents positive mass of observations at that extreme, and is unbounded otherwise. In a subsequent study, the authors explore the relative weights of different types of metrics in bonus plans for business unit managers (Indjejikian and Matějka 2012). While the variables reported in their study present similar characteristics to the previous one (i.e. bounded variables with single fat tails), the relation between the dependent variables and the predictors is modeled using weighted least squares estimation. Although this method accounts for error clustering, it still is a linear estimation method. Du et al. (2013) estimate a path model using partial least squares (PLS) to analyze the influence of headquarters-subsidiary interdependence on the use of participative performance evaluation mechanisms. Using survey data collected from a sample of industrial firms, van Veen-Dirks (2010) finds a significant difference in the importance attributed to performance metrics depending on whether such metrics are collected for performance evaluation purposes or for reward purposes. Hartmann et al. (2010) use PLS to estimate the relation between leadership style and the use of performance metrics on goal clarity, job satisfaction, and perceived fairness.

Several survey-based studies focus on the determinants and the consequences of adopting certain types of management control systems. King and Clarkson (2015) estimate an ordinal logistic regression model of the fit of management control systems and self-reported measures of organizational performance. Henri (2010) uses OLS to estimate the relation between organizational characteristics, such as dynamism of management control systems and strategic capabilities, and the extent to which performance indicators are reviewed by organizations.

Another example of survey research that employs bounded response variables is Graham et al. (2011), which uses survey responses from tax executives to examine corporate decisions related to real investment location and profit repatriation. Their survey uses a five-point scale to examine the importance of the foreign tax rate, U.S. cash tax deferral, and financial accounting expense deferral under APB 23 in firms' decisions about locating operations in or outside the U.S. Survey response variables that use such Likert-type scales are bounded by design and display positive probability mass at the extremes. The authors then use OLS regressions to estimate a model where the dependent variables are the survey ratings.

Relations involving bounded response variables of interest for accounting researchers are often non-linear in nature and likely to display some degree of nonconstant marginal effects. Allowing for non-linearity in the functional form is important for the estimation of nonconstant marginal effects and provides a better fit and specification of the model compared to linear estimation approaches, such as OLS or Tobit. Additionally, positive mass at the extremes of the distribution may be of particular interest to accounting researchers. Among the family of nonlinear models, the FRM is relatively easy to estimate, allows for heterogeneity in the predictors, and provides information on both point and average partial effect. Additionally, due to its computational simplicity, the FRM can be used to supplement traditional linear models at a relatively low cost.

IV. ILLUSTRATION: FRM APPLIED TO A STUDY OF PATIENT SATISFACTION

Firms frequently use nonfinancial performance measures such as customer satisfaction as an integral element of their planning, performance measurement, and compensation systems. Extant accounting literature finds evidence that customer satisfaction is a lead indicator of future financial performance (Ittner and Larcker 1998; Lambert 1998; Banker and Mashruwala 2007).

Customer satisfaction has a positive effect on customer retention and thereby increases future revenues (Banker et al. 2000). Customer satisfaction is generally measured with surveys that use Likert-based scales. In the health care industry, patient satisfaction is not only an important driver of hospital and patient outcomes, but public reporting of patient satisfaction is required under the Affordable Care Act of 2010.

We utilize patient satisfaction data from a system of public hospitals in Japan to illustrate how the FRM can help to overcome limitations of other established econometric approaches. In particular, we examine the influence of selected organizational characteristics on the level of patient satisfaction over time. We select a subset of patient satisfaction dependent variables to simplify the exposition of our findings.[7] Our goal is to provide econometric results that illustrate the advantages and incremental information provided by the FRM.

Sample and Variables

We use a panel of proprietary patient satisfaction data obtained from the National Health Organization (NHO), an Independent Administrative Institution (IAI) that coordinates and oversees 145 public hospitals in Japan. In 2004, the NHO introduced a mandatory annual patient satisfaction survey. The survey comprises of separate questionnaires for inpatients and outpatients. Some questions are specific to the inpatient vs. outpatient experience, while others are common to both inpatients and outpatients. Questions cover topics related to clinical, logistic, and administrative aspects of the patient's experience with the individual hospital. Patients are asked to express their degree of agreement with given statements about their satisfaction with the service they received by means of a 5-point Likert-scale (where a score of 1 corresponds to

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[7] A complete analysis of the drivers of patient satisfaction and their improvement over time is in Gallani et al. (2016)

complete dissatisfaction, and a score of 5 corresponds to complete satisfaction).[8] The survey is administered by an independent agency, which collects and processes the data for all NHO hospitals. Hospitals receive feedback reports that provide information about their satisfaction performance both in absolute terms and relative to all other member hospitals. We selected two specific questions from the inpatient questionnaire as dependent variables for the purpose of this empirical illustration. The first question assesses patient satisfaction with the surgical treatment received, while the second question relates to patients satisfaction with the duration of their treatment at the hospital. We selected these two items because the distribution of their responses is representative of the problems that arise in survey-based studies in accounting.

As in many Likert-based surveys, the responses are not normally distributed. Non-normal distributions are a bane of survey-based studies.[9] Figure 1 shows the distribution of the ratings for each item. A visual comparison of the figure in Panel A (satisfaction with the surgical treatment) and the one in Panel B (satisfaction with the duration of the treatment) highlights the presence of a fat tail in the former, while the latter, albeit visibly left-skewed, does not exhibit a material mass of observations at the upper bound. We expect to obtain the largest informative advantages from the FRM in cases where there is significant pile-up at one of the extremes.

The predictor variables include a binary variable *Hospital*, assuming the value 0 if the healthcare facility is a sanatorium (a type of Japanese hospital that, in addition to providing all the services of a regular hospital, specializes in complex, high-risk, long term ailments, such as cancer, terminal illness, chronic mental illnesses, etc.), and the value 1 if the organization is a

[8] These scales have quantitative meaning and represent an underlying continuous distribution of satisfaction, as they *quantify* the degree of satisfaction in *increasing* levels.
[9] For example, when survey questionnaires are used for evaluation purposes (employee performance, customer satisfaction, etc.), researchers commonly observe a leniency bias, which refers to the tendency to rate others higher than they deserve (Podsakoff et al. 2003).

general hospital; *Size*, a standardized variable measuring the number of beds in each hospital; *Competition*, a standardized variable measuring the number of hospitals per-capita in the prefecture (a geographical unit equivalent to a county in the US) where each hospital is located. *Inpatient Revenue, Total Costs,* and *Total Grants*, are expressed in billions of yen. In particular, *Total Grants* represent the amount of public subsidy the hospital receives in support of their research and infrastructure needs. Because our data includes observations for 8 consecutive years, we control for time with a *Trend* variable. Table 2 reports descriptive statistics for the dependent variables and predictors described above.

---- Insert Table 2 here ----

Statistical Analyses and Results

We apply a linear transformation to the scores to the dependent variables that are, in both cases, bounded between 1 and 5. The transformation converts each dependent variable to fall between 0 and 1.[10] We estimate the following model:

$$\begin{aligned} Sat_i = \alpha + \beta_1 Trend_i + \beta_2 Hospital_i + \beta_3 Size_i + \beta_4 Competition_i + \beta_5 Inpatient\_revenue_i + \\ + \beta_6 Total\_Costs_i + \beta_7 Total\_Grants_i + \varepsilon_i \end{aligned} \tag{1}$$

where Sat_i refers to patient satisfaction with the surgical treatment and, in a separate estimation of the model, satisfaction with the duration of the treatment.

We estimate equation (1) using OLS as well as the FRM.[11] Because none of our bounded dependent variables presents pile-up at *both* extremes we do not use two-limit Tobit, which

[10] Each score is transformed by subtracting the minimum point of the scale (1) and dividing by the distance between minimum and maximum points on the scale (5 – 1 = 4).

[11] In the analysis of panel data with large cross-sections and small number of years, Papke and Wooldridge (2008) recommend the use of probit FRM (f-probit), which allows for unobserved exogeneity and provides consistent estimations without including separate intercepts to account for firm fixed effects.

would provide logically inconsistent estimations in our settings. Table 3 reports the estimation results.

We first turn to the results for patient satisfaction with surgical treatment. Panel A of Table 3 reveals that, when we estimate the model using OLS, *Hospital, Size,* and *Competition* are positively associated with patient satisfaction, while *Total_Grants* are significantly negatively associated. OLS and FRM, for the most part, reveal similar results in terms of significance and direction of the effects of the predictors, with the exception of *Total_Costs,* which is a significant positive predictor of satisfaction only when we estimate the model using the FRM. Panel B reports the coefficients estimated for equation (1) when the dependent variable measures patient satisfaction with the duration of the treatment. Significance and direction of the coefficients are consistent across the two estimation methods.

---- Insert Table 3 here ----

The comparison of the R^2 values associated with the two approaches (Table 3) indicates that the FRM estimation systematically yields a better fit than OLS.[12] This is because the FRM accounts for the nonlinearity in the data, as well as for the boundedness of the dependent variable.

Additionally, the analysis of the partial effects shows how the FRM can be instrumental to more accurate inferences, especially at the tails of the response variable distribution. The OLS estimation predicts constant changes in the response variable driven by a unit change in the predictors, independent of the starting value of the explanatory variable. The FRM accounts for nonconstant returns. The analysis of the average partial effects (APE) shows that when the

[12] QMLE estimation does not aim at maximizing the R^2. Commonly used statistical packages do not report R^2 as part of the output of glm model estimations. We, therefore, calculate R^2 by squaring the correlation between the observed dependent variable (*y*) and the predicted dependent variable (*y-hat*).

distribution of the response variable exhibits a larger mass at the upper bound, there is a significant difference between the APE calculated with FRM estimation and the coefficients estimated with OLS (Table 3, Panel A). As opposed to this, when the distribution of the response variable has little mass at the upper bound, the differences between the FRM and OLS are not as salient (Table 3, Panel B).

While the overall average partial effect (APE) is reasonably comparable to the coefficients estimated by OLS, the analysis of partial effects at various percentiles of the predictor's distribution provides insights on the shape of the relation between the explanatory and response variables, as summarized in Table 3, Panels A and B. The satisfaction with the surgical treatment, for example, shows a progressive deceleration with respect to of *Size*, whereas satisfaction with the duration of the treatment accelerates as *Size* increases. Further examination of hospital care processes reveals that larger hospitals have more standardized procedures and less personalized care; therefore the effect of an increase in hospital size might offer diminishing improvements in satisfaction with the treatment. With respect to duration of treatment, larger hospitals have better infrastructure and resources to provide more efficient cycles of care (e.g. physical therapists might be available during the weekend in larger hospitals, where a larger number of physical therapists can service patients on a more continuous timeline), hence driving shorter treatment durations. Results also indicate that the effect of *Competition* exhibits diminishing returns to satisfaction for both satisfaction and duration. The effect of *Total Grants* appears to accelerate past the median point in both cases. Because grants are intended to support research and improvements in the infrastructure, it is plausible that greater focus on research distracts medical personnel from exhibiting behaviors that drive patient satisfaction (such as bedside manner, or time spent with each patient), while infrastructural improvements might cause delays and complications to the logistics associated with the cycle of care that might be reflected in the satisfaction rating with respect to the duration of the treatment. In sum, the FRM provides better fit than OLS on the shape of the relation between patient satisfaction and its drivers.

V. SUMMARY AND CONCLUSIONS

In this paper we present some key features of the fractional response model (FRM) developed by Papke and Wooldridge (1996, 2008), discuss its application to a variety of phenomena of interest for accounting researchers, and propose its application to survey-based studies. The FRM overcomes limitations of existing alternative approaches for the statistical analysis of dependent variables that are bounded in nature and present a material number of corner observations. The FRM is computationally simple, offers interesting levels of flexibility in its applications to cross-sectional, longitudinal, and panel data, accounts for nonlinearity, and rests free of many of the restrictive assumptions that are in general required by more traditional econometric solutions.

Accountants are often interested in studying variables that are bounded in nature and exhibit positive probability mass at one of the bounds (single fat tails). Examples include accounting based performance measures such as market share, accounting and reporting choices such as the percentage of goodwill written off, executive compensation contract composition, or the portion of foreign earnings that are permanently reinvested. Survey-based studies in accounting often collect data by means of Likert scales that are built to represent progressive levels of agreement/disagreement with a provided statement. Empirical analyses reported in the literature generally relay on linear regressions or ordered logit and probit models. Respondent characteristics and biases often drive accumulation of responses at one of the extremes of the scale. We posit that, when the scale items have quantitative meaning and represent an underlying continuous distribution, and a material portion of observations lies at one of the boundaries, the FRM provides better functional specification and fit than estimation methods traditionally observed in the literature. We present simulation results that reveal the estimation advantage provided by the FRM for varying levels of mass at the boundaries.

To provide an illustration of the FRM in an accounting setting we analyze patient satisfaction data recorded by 145 public hospitals in Japan in eight consecutive years subsequent to the introduction of a mandatory performance measurement and reporting system. We perform the estimation of our statistical models using both OLS and the FRM. Comparison of the results indicates that the FRM provides improved fit while accounting for the nonlinearity in the data and the nonconstant returns of the dependent variable along the range of the predictors. Additionally, the evaluation of average partial effects at different levels of the explanatory variables shows that the FRM supports more precise inferences, especially in cases where observations at the end of the distribution are of particular interest for the researcher. Given the computational simplicity and the incremental explanatory power, the application of the FRM should be considered at least as a complement to other traditional econometric methods used in survey-based accounting research.

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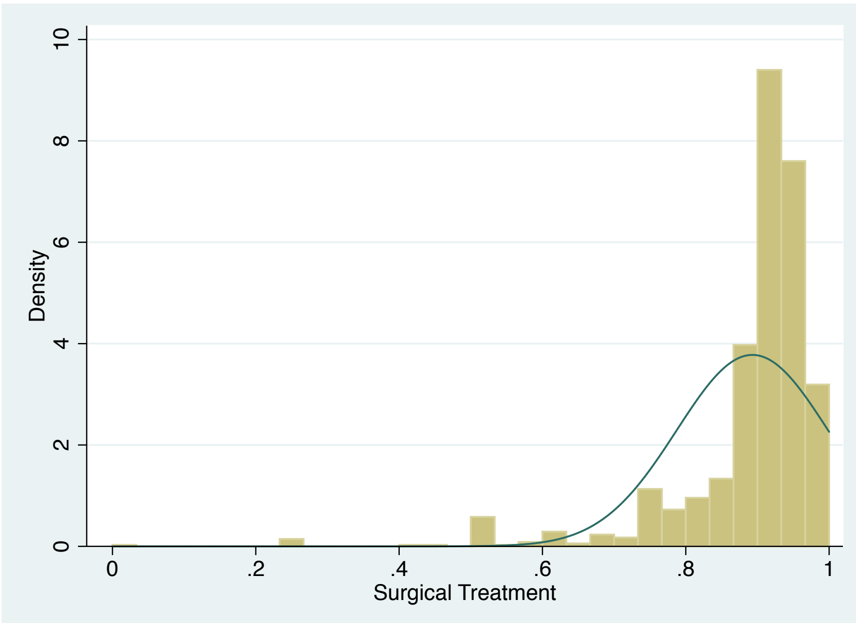
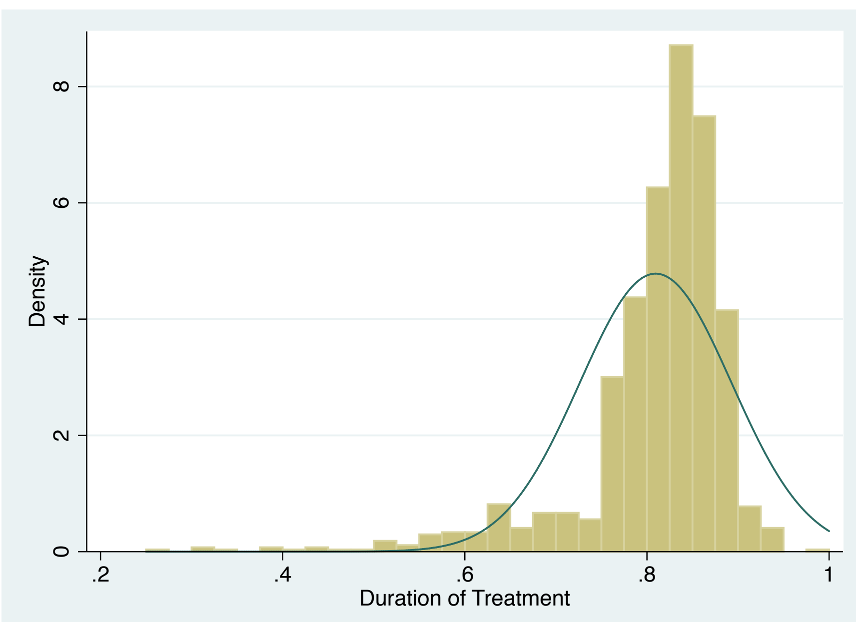
FIGURE 1:

Panel A: Satisfaction with the surgical treatment



Panel B: Satisfaction with the duration of the treatment



Notes: The horizontal axis measures the satisfaction score as a percentage of the range between the minimum and maximum satisfaction scores available in the Likert-scale instrument.

TABLE 1
Simulation results: comparison between OLS, Tobit and FRM

Probability distribution of *x*	*f*	Mass at corners	OLS		Tobit		Fractional Response Model (FRM)							
			R^2	$\hat{\beta}_{OLS}$	R^2	$\hat{\beta}_{Tob}$	R^2	$\hat{\beta}_{FRM}$	APE	APE (1%)	APE (5%)	APE (50%)	APE (90%)	APE (99%)
Normal	x	0.166	0.295	0.834	0.295	1.001	0.296	3.766	0.835	0.472	0.652	0.941	0.655	0.473
	2x	0.317	0.579	1.365	0.579	1.999	0.600	7.957	1.365	0.189	0.502	1.987	0.507	0.189
	x^2	0.104	0.001	0.002	0.001	0.002	0.001	0.007	0.002	0.002	0.002	0.002	0.002	0.001
	$x^{1/2}$	0.205	0.156	0.549	0.156	0.679	0.158	2.616	0.549	0.615	0.649	0.573	0.365	0.283
	exp(x)	0.169	0.297	0.839	0.297	1.013	0.297	3.793	0.839	0.493	0.677	0.947	0.634	0.451
	ln(x)	0.171	0.304	0.850	0.304	1.032	0.304	3.860	0.850	0.447	0.633	0.963	0.684	0.492
Beta	x	0.220	0.218	0.813	0.218	0.996	0.219	3.805	0.764	0.814	0.925	0.786	0.512	0.465
	2x	0.257	0.479	1.463	0.479	1.999	0.494	7.777	1.485	0.214	0.507	1.934	1.202	0.999
	x^2	0.180	0.327	1.121	0.327	1.336	0.332	5.078	1.099	0.528	0.811	1.254	0.880	0.790
	$x^{1/2}$	0.160	0.089	0.508	0.089	0.621	0.089	2.341	0.523	0.330	0.395	0.543	0.584	0.585
	exp(x)	0.266	0.507	1.519	0.507	1.984	0.515	7.766	1.451	0.347	0.775	1.868	0.841	0.676
	ln(x)	0.234	0.395	1.238	0.395	1.555	0.399	5.898	1.162	0.649	1.041	1.326	0.693	0.591
Poisson	x	0.182	0.338	0.082	0.338	0.100	0.341	0.381	0.082	0.055	0.069	0.095	0.056	0.034
	2x	0.353	0.612	0.129	0.612	0.201	0.643	0.804	0.129	0.028	0.058	0.201	0.029	0.007
	x^2	0.293	0.258	0.062	0.258	0.098	0.250	0.368	0.066	0.088	0.919	0.069	0.024	0.014
	$x^{1/2}$	0.186	0.029	0.019	0.029	0.023	0.029	0.093	0.019	0.022	0.021	0.019	0.016	0.015
	exp(x)	0.307	0.497	0.106	0.497	0.163	0.519	0.629	0.111	0.071	0.107	0.141	0.024	0.008
	ln(x)	0.381	0.557	0.125	0.557	0.203	0.619	0.776	0.127	0.038	0.074	0.191	0.025	0.007

Notes to Table 1: (1) This table reports the results of a Monte Carlo simulation performed using Stata. The dependent variable is defined considering $y = \min(y^*, 1)$ and $y = \max(0, y^*)$, where $y^* = \alpha + f(x) + u$. Each simulation run involves 200 repetitions of samples of 1,000 observations. We manipulate the type and parameters of the distribution from which observations are randomly extracted. We also manipulate the function *f* linking predictor and response variable. In all scenarios the error term is obtained from a normal distribution: $u \sim N(0,.3)$. The estimation results reflect the means calculated for all parameters and statistics of interest in each run of 200 repetitions. The percentage of observations at the corners refers to the sum of the observations at each corner, divided by the total number of observations. The values of the estimated slope coefficients ($\hat{\beta}$) are reported for OLS and Tobit, which are linear models and, as such, predict a constant change in the response variable for any unit change in the predictor, independently from the percentile of the distribution of the predictor. The value of $\hat{\beta}$ in FRM is not representative of the economic significance of the effect, because in nonlinear models the slope might be different at every value of the predictor. The average partial effect (APE) is comparable to the values of $\hat{\beta}$ in OLS and Tobit. Additionally, we report the APE at various percentiles of the distribution of the predictor to illustrate how the FRM accounts for nonlinearity in the data.

TABLE 2
Illustration of FRM application to a study of determinants of patient satisfaction - Descriptive statistics

Dependent Variables	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**	**1st pct**	**5th pct**	**Median**	**95th pct**	**99th pct**
Satisfaction with Surgical Treatment	1034	0.893	0.106	0.000	1.000	0.500	0.700	0.920	1.000	1.000
Satisfaction with the Duration of Treatment	1079	0.810	0.083	0.250	1.000	0.486	0.633	0.830	0.897	0.931

Predictor Variables	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**	**1st pct**	**5th pct**	**Median**	**95th pct**	**99th pct**
Hospital	1152	0.403	0.491	0.000	1.000	0.000	0.000	0.000	1.000	1.000
Size	1152	0.000	1.000	-1.922	2.898	-1.654	-1.473	-0.171	1.957	2.724
Competition	1152	0.000	1.000	-1.369	3.593	-1.369	-1.216	-0.262	1.799	2.562
Inpatient Revenue	999	4.276	2.666	0.905	15.581	1.095	1.467	3.633	10.790	13.120
Total Costs	1142	5.085	3.368	0.675	19.473	1.370	1.681	4.119	12.652	16.938
Total Grants	1141	0.031	0.046	0.000	0.438	0.000	0.000	0.016	0.114	0.225

Notes: Table 2 reports descriptive statistics for the variables included in equation (1):

$$Sat_i = \alpha + \beta_1 Trend_i + \beta_2 Hospital_i + \beta_3 Size_i + \beta_4 Competition_i + \beta_5 Inpatient\_revenue_i +_6 Total\_Costs_i + \beta_7 Total\_Grants_i + \varepsilon_i$$

(1) The dependent variables are selected from a proprietary dataset of patient satisfaction data collected over 8 years by Japanese public hospitals, subsequent to the introduction of a mandatory annual patient satisfaction survey. The survey response are collected using a 5-point Likert scale, where a score of 1 indicates complete dissatisfaction and a score of 5 indicates complete satisfaction. (2) Predictor variables represent organizational characteristics of each hospital. The indicator variable *Hospital* assumes the value 0 if the site is a sanatorium (a particular type of Japanese hospital that, in addition to providing healthcare services typical of a general hospital, specializes in complex, high-risk, long term ailments, such as cancer, terminal illness, chronic mental illnesses, etc.), and the value 1 if the organization is a general hospital; *Size* is a standardized variable measuring the number of beds in each hospital; *Competition* is a standardized variable measuring the number of hospitals per-capita in the prefecture (a geographical unit equivalent to a county in the US) where each hospital is located. *Inpatient Revenue, Total Costs,* and *Total Grants*, are expressed in billions of yen. In particular, *Total Grants* represent the amount of public subsidy the hospital receives in support of their research and infrastructure needs. The variable *Trend* allows us to control for the changes in patient satisfaction due to the mere passage of time. For each variable we report values observed at the 1^{st}, 5^{th}, 95^{th}, and 99^{th} percentiles, in addition to mean, median, standard deviation, minimum and maximum values observed.

TABLE 3
Drivers of Patient Satisfaction

Panel A: DV = Satisfaction with Surgical Treatment

	OLS	FRM	APE	APE at trend = 1	APE at trend = 2	APE at trend = 3	APE at trend = 4	APE at trend = 5	APE at trend = 6	APE at trend = 7	APE at trend = 8
Trend	0.003* [0.002]	0.015* [0.008]	0.0026	0.0029	0.0028	0.0028	0.0027	0.0026	0.0026	0.0025	0.0025
			APE	**APE at 1st pct**	**APE at 5th pct**	**APE at 50th pct**	**APE at 95th pct**	**APE at 99th pct**			
Hospital	0.038*** [0.008]	0.197*** [0.042]	0.0343	0.0379	0.0379	0.0379	0.0295	0.0295			
Size	0.015** [0.006]	0.070** [0.032]	0.0122	0.0141	0.0138	0.0123	0.0101	0.0095			
Competition	0.012*** [0.003]	0.070*** [0.016]	0.0122	0.0137	0.0135	0.0125	0.0103	0.0096			
Inpatient Revenue	-0.005 [0.004]	-0.036 [0.029]	-0.0064	-0.0050	-0.0056	-0.0062	-0.0084	-0.0090			
Total Costs	0.005 [0.003]	0.042* [0.023]	0.0073	0.0089	0.0087	0.0077	0.0044	0.0033			
Total Grants	-0.108* [0.060]	-0.671** [0.333]	-0.1169	-0.1136	-0.1136	-0.1154	-0.1257	-0.1392			
Intercept	0.865*** [0.009]	1.080*** [0.053]									
N	896	896									
R^2	0.099	0.113									
Difference in R^2		14.1%									

Panel B: DV = Satisfaction with the Duration of Treatment

	OLS	FRM	APE	APE at trend = 1	APE at trend = 2	APE at trend = 3	APE at trend = 4	APE at trend = 5	APE at trend = 6	APE at trend = 7	APE at trend = 8
Trend	0.004*** [0.001]	0.013*** [0.004]	0.0036	0.0037	0.0037	0.0037	0.0037	0.0036	0.0035	0.0035	0.0034
			APE	**APE at 1st pct**	**APE at 5th pct**	**APE at 50th pct**	**APE at 95th pct**	**APE at 99th pct**			
Hospital	0.015*** [0.006]	0.054** [0.021]	0.0144	0.0147	0.0147	0.0147	0.0140	0.0140			
Size	-0.006 [0.004]	-0.025 [0.016]	-0.0068	-0.0065	-0.0065	-0.0067	-0.0070	-0.0072			
Competition	0.017*** [0.002]	0.065*** [0.008]	0.0174	0.0188	0.0185	0.0177	0.0156	0.0148			
Inpatient Revenue	0.001 [0.002]	0.003 [0.010]	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008			
Total Costs	0.006*** [0.002]	0.024*** [0.008]	0.0064	0.0069	0.0068	0.0065	0.0053	0.0048			
Total Grants	-0.173*** [0.055]	-0.642*** [0.195]	-0.1709	-0.1676	-0.1676	-0.1694	-0.1793	-0.1915			
Intercept	0.760*** [0.008]	0.690*** [0.030]									
N	940	940									
R^2	0.142	0.152									
Difference in R^2		7.0%									

Notes: Table 3 reports the results of the estimation of the model in equation (1)

$$Sat_i = \alpha + \beta_1 Trend_i + \beta_2 Hospital_i + \beta_3 Size_i + \beta_4 Competition_i + \beta_5 Inpatient\_revenue_i +_6 Total\_Costs_i + \beta_7 Total\_Grants_i + \varepsilon_i$$

using both OLS estimation and the FRM. We report average partial effects (APE) both with respect to the overall distribution of each predictor, as well as at the 1^{st}, 5^{th}, 50^{th}, 95^{th}, and 99^{th} percentiles of each predictor. Because the explanatory variable *Trend* is discrete, we report APE at each of the values that *Trend* assumes in our sample. *Panel A* reports the estimated coefficients for the model described in Equation (1) when the dependent variable measures patient satisfaction with the surgical treatment. *Panel B* reports the results of the estimation of the model when the dependent variable measures patient satisfaction with the duration of hospital treatment. For the FRM, R^2 is calculated as the square of the correlation coefficient between the observed values of the dependent variable (y) and the predicted variable (y-*hat*). Statistical significant levels are indicated by *** ($p<0.01$), **($p<0.05$), *($p<0.10$)