Economics Bulletin

Volume 44, Issue 3

A tax evasion experiment revisited

Jonas Andersson
Norwegian School of Economics

Abstract

In this paper the experimental data collected by Masclet, Montmarquette and Viennot-Briot (2019a) is revisited in order to study some aspects of the drivers of the declaration rate, not studied in the authors´ article. By using a zero-one inflated beta regression model, a more detailed analysis of the special values, zero declaration and full declaration, is enabled. It turns out that some of the drivers of the declaration rate is affecting the three parts of the declaration rate distribution, the zero declarers, the full declarers and the intermediate declarers, differently. It is found that the effect of tax payers' monitoring, i.e., their knowledge about other tax payers' evasion, increases the probability to declare zero. Among the individuals declaring a part of their income, the effect is significantly positive; they declare more. Another result is that, for the average experiment participant, both the probability to fully declare or declare nothing of the income is increasing as the experiment progresses.

The author gratefully acknowledges valuable comments from Jan Ubøe.
Citation: Jonas Andersson, (2024) "A tax evasion experiment revisited", *Economics Bulletin*, Volume 44, Issue 3, pages 1010-1017
Contact: Jonas Andersson - jonas.andersson@nhh.no.
Submitted: March 07, 2024. **Published:** September 30, 2024.

1 Introduction

Working to make sure that taxes are collected in the spirit of the law or, at the very least, according to the law, is essential for a well functioning government. In order to do this work constructively, studies of tax evasion behavior are needed. One strand of this literature is based on experiments. For examples and reviews of laboratory experiments, see e.g. Masclet, Montmarquette, and Viennot-Briot (2019a), Pickhardt and Prinz (2014), Gërxhani and Schram (2006), Alm and Malézieux (2021), Malézieux (2018) and Alm (2012). Examples of the literature on field experiments are Bott et al. (2020), Bérgolo et al. (2017) and Bjørneby, Alstadsæter, and Telle (2021). In this paper the data collected by Masclet, Montmarquette, and Viennot-Briot (2019b), generously made availble from the authors at Mendeley, will be revisited.

The tax declaration rate is a number between, and including, zero and one. If values are on the boundary of this interval, zero or one, this means that either nothing or all of the income is declared. In combination with seeing tax evasion as a decision problem in the spirit of Allingham and Sandmo (1972), this leads to an interesting question, namely, if there are some special, some remarkable, features of the observations with exactly zero and one tax declaration rate, respectively. Are the drivers for choosing a corner solution (zero or one) the same as the drivers for choosing a fractional solution to the decision problem?

The aim of this paper is to shed light on this question, or more specifically, to investigate if the treatments, monitoring and peer reporting, and other covariates, in the experiment by Masclet, Montmarquette, and Viennot-Briot (2019a), affect the zero and full declarers[1] in the same way as the intermediate declarers. This is done by means of a zero-one inflated beta regression model where the probability for zero and full declaration are explicitly modelled. In the paper by Masclet, Montmarquette, and Viennot-Briot (2019a), a Tobit regression, where values below zero and above one were considered to be censored, was used.

In the next section, the zero-one inflated beta regression model, and how to estimate it, is reviewed. In Section 3 the model is used to answer the posed question. A conclusion ends the paper.

2 The zero-one inflated beta regression model

We would like to model the relationship between a scalar stochastic variable Y with support on $[0, 1]$ (note the inclusion of the endpoints) and a vector of explanatory variables $\boldsymbol{X}$.

A natural starting point for the conditional distribution of $(Y|\boldsymbol{X} = \boldsymbol{x})$ is the beta distribution since its support is $(0, 1)$. However, since our variable Y has a support including the endpoints 0 and 1, the model needs to be modified. This was done, e.g., in Ospina and Ferrari (2012). Starting with the standard formulation of the beta-distribution

$$f(y; \alpha, \beta) = \begin{cases} \dfrac{1}{B(\alpha, \beta)} y^{\alpha-1}(1-y)^{\beta-1} & \text{if } 0 < y < 1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

the model is reparametrized in order to get a parameter representing the mean

$$\begin{cases} \mu = \dfrac{\alpha}{\alpha+\beta} \\ \phi = \dfrac{1}{\alpha+\beta+1} \end{cases} \iff \begin{cases} \alpha = \dfrac{\mu(1-\phi)}{\phi} \\ \beta = \dfrac{(1-\mu)(1-\phi)}{\phi} \end{cases} \tag{2}$$

and obtain

$$f(y; \mu, \phi) = \begin{cases} \dfrac{1}{B\left(\frac{\mu(1-\phi)}{\phi}, \frac{(1-\mu)(1-\phi)}{\phi}\right)} y^{\frac{\mu(1-\phi)}{\phi}-1}(1-y)^{\frac{(1-\mu)(1-\phi)}{\phi}-1} & \text{if } 0 < y < 1 \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

[1]The term *declarer* is used even though it is recognized that an individual in the experiment can declare different rates in different periods of the experiment.

Inclusion of covariates, $\boldsymbol{x}$ (p-vector) is now straightforward, by letting μ be a function of these. A natural choice of link-function is the logistic function since μ is the expected value of a stochastic variable with support on $(0, 1)$.

$$\mu(\boldsymbol{x}) = \frac{1}{1 + e^{-\boldsymbol{x}'\boldsymbol{\gamma}}} \tag{4}$$

In some applications, such as the one in this paper, there are two clusters of observations outside of the support of the beta distribution, namely for the values $Y = 0$ and $Y = 1$. This can be accommodated for by using a multinomial (trinomial) logit model. We introduce three dummy variables Z_{z} (z for zero), Z_{m} (m for middle) and Z_{o} (o for one) defined so that if $Y = 0$, then $(Z_{\mathrm{z}}, Z_{\mathrm{m}}, Z_{\mathrm{o}}) = (1, 0, 0)$, if $Y \in (0, 1)$, then $(Z_{\mathrm{z}}, Z_{\mathrm{m}}, Z_{\mathrm{o}}) = (0, 1, 0)$ and if $Y = 1$ then $(Z_{\mathrm{z}}, Z_{\mathrm{m}}, Z_{\mathrm{o}}) = (0, 0, 1)$

$$P(Z_{\mathrm{z}} = z_{\mathrm{z}}, Z_{\mathrm{m}} = z_{\mathrm{m}}, Z_{\mathrm{o}} = z_{\mathrm{o}}) = p_{\mathrm{z}}^{z_{\mathrm{z}}} p_{\mathrm{m}}^{z_{\mathrm{m}}} p_{\mathrm{o}}^{z_{\mathrm{o}}} \tag{5}$$

The probabilities for the three alternatives should sum to one so that $p_z + p_m + p_o = 1$. We will in the sequel, therefore, only consider p_z and p_o, the probability for a zero- and a one-observation, respectively.

Also these probabilities can be functions, e.g., logistic functions, of the covariates $\boldsymbol{x}$.[2]

$$\begin{cases} p_z(\boldsymbol{x}) = \dfrac{e^{\boldsymbol{x}'\boldsymbol{\delta}_z}}{1 + e^{\boldsymbol{x}'\boldsymbol{\delta}_z} + e^{\boldsymbol{x}'\boldsymbol{\delta}_o}} \\ p_o(\boldsymbol{x}) = \dfrac{e^{\boldsymbol{x}'\boldsymbol{\delta}_o}}{1 + e^{\boldsymbol{x}'\boldsymbol{\delta}_z} + e^{\boldsymbol{x}'\boldsymbol{\delta}_o}} \end{cases} \tag{6}$$

The probability density for Y given $\boldsymbol{X} = \boldsymbol{x}$ can now be written

$$f(y|\boldsymbol{x}, \boldsymbol{\gamma}, \phi, \boldsymbol{\delta}_z, \boldsymbol{\delta}_o) = p_z(\boldsymbol{x}) I(y = 0) + (1 - p_z(\boldsymbol{x}) - p_o(\boldsymbol{x})) f_{\mathrm{Beta}}(y|\boldsymbol{x}) + p_o(\boldsymbol{x}) I(y = 1) \tag{7}$$

where f_{Beta} is based on the parametrization in equation (3). Based on this density, maximum likelihood estimation can be done. In this paper, the `R`-package `gamlss` is used, see Rigby and Stasinopoulos (2005). The package also allows for the inclusion of random effects.

3 Results

First, I will analyze the unconditional distribution of the dependent variable, the declaration rate, `txdeclare`. Figure 1 shows a histogram of the variable.

[2]There might, of course, be differences in which covariates are used to explain μ, p_z and p_o but to simplyfy notation, only one set of covariates, $\boldsymbol{x}$, are used in this exposition.

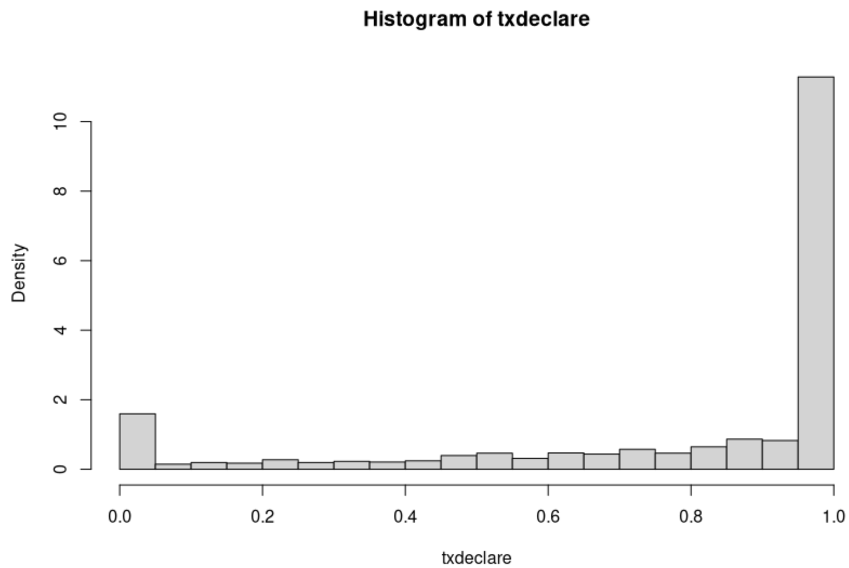
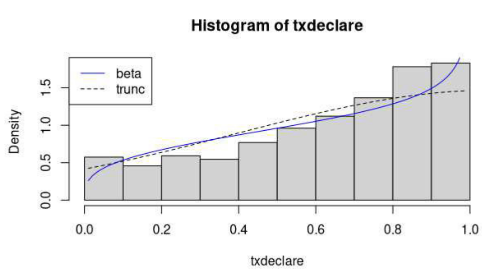
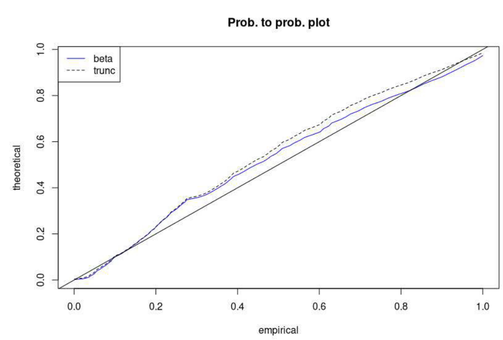


Figure 1: Histogram of txdeclare

As can be seen, the probabilities for zero and full declaration, are substantial. In Figure 2, the zeroes and ones are not shown. On top of the histogram in Figure 2a, and the probability to probability (PP) plot in Figure 2b lies graphs of the truncated normal and the zero-one inflated beta distribution fitted to all the observations (including the zeroes and ones).



(a) Histogram



(b) PP-plot

Figure 2: Histogram and PP-plot of declaration rate with fitted beta and truncated normal distributions.

It might be argued that, in the absense of covariates, the beta distribution fits these observations better. A more important point, though, is that the zero-one inflated beta distribution enables us to study the frequently observed, zero and full declaration rates, as well. I will, thus, not only take the large probabilities for zero and full declaration, visible in Figure 1 into account to estimate the rest of the conditional distribution correctly; I will also model these probabilities explicitly. The truncated normal distribution, on which the tobit model is based, is not able to do that.

I now create a variable, `state`, derived from the variable `txdeclare`. It attains the value `zero` if `txdeclare` is zero, `intermediate` if `txdeclare`is in $(0, 1)$ and `full` if `txdeclare` is one. The relative frequencies of the values are shown in Table 1.

Table 1: Shares of zero, intermediate and full declaration of income.

State	zero	intermediate	full
Share	0.064	0.405	0.531

When conditioned on the treatment groups, a more nuanced pattern emerges. This is shown in Table 2. Evidently, there is a larger fraction in the monitoring group who declares zero and a larger fraction who fully declares in the peer reporting group. This corresponds well with the results by Masclet, Montmarquette, and Viennot-Briot (2019a) found this result by using a tobit regression with random individual effects and controls for some other covariates.

Table 2: Shares of zero, intermediate and full declaration of income for each treatment group.

State	zero	intermediate	full
Base	0.063	0.448	0.489
Peer report	0.013	0.325	0.662
Monitoring	0.116	0.441	0.444

By fitting a zero-one-inflated beta regression, as a starting point only with treatment dummies, we notice that there are some nuances to this result (that monitoring yields a lower declaration rate), see tables 3, 4 and 5. In order to see this, I consider the μ-equation, signifying the expected declaration rate conditional on the fact that neither zero nor full declaration has been made. In this case, monitoring has a significant positive effect[3], as opposed to the overall results in Masclet, Montmarquette, and Viennot-Briot (2019a). The base treatment subjects have an expected declaration rate of 0.554 while the monitoring group has an expected rate of 0.590. Peer reporting still has a large positive effect. The explanation for the difference in the results is seen when we consider the p_z-equation, i.e., the conditional probability for zero declaration. Here we see that monitoring is significantly increasing the probability for zero declaration. While the base group has an expected zero-probability of 0.063, the monitoring group has a corresponding value of 0.116. Peer reporting, on the other hand, is decreasing it. On the other end of the scale we see that the probability for full declaration, shown by the p_o-equation, is significantly increased by peer reporting (0.489 for the base group while 0.662 for the peer reporting group) but only weakly, negatively, affected by monitoring. These probabilities, given by the estimated coefficients plugged into the formulas in (6), are identical to the observed frequencies of conditional zero and full declaration shown in Table 2. This will change in the next subsections, where I will add covariates.

Table 3: μ-equation. The estimated effects of the treatments for the intermediate declarers, see the γ-coefficients in (4).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	0.217	0.030	7.330	0.000
Peer reporting	0.657	0.046	14.223	0.000
Monitoring	0.147	0.042	3.483	0.000

Table 4: p_z-equation. The estimated effects of the treatments for the null declarers, see the δ_z-coefficients in (6).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	-1.959	0.079	-24.744	0.000
Peer reporting	-1.300	0.187	-6.937	0.000
Monitoring	0.621	0.100	6.194	0.000

[3]If nothing else is said, a significant coefficient refers to refers to significance on the 5% significance level.

Table 5: p_o-equation. The estimated effects of the treatments for the full declarers, see the δ_o-coefficients in (6).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	0.086	0.039	2.233	0.026
Peer reporting	0.625	0.055	11.259	0.000
Monitoring	-0.079	0.055	-1.429	0.153

As can be seen in the tables 9, 10 and 11 in the appendix, the results does not, qualitatively, change by including random effects in (4) and (6). However, the numbers changes to some extent, implying that the random-effects model does not produce exactly the conditional probabilities for zero and full declaration in Table 2. The following analysis is done without random effects.

After adding covariates used in Masclet, Montmarquette, and Viennot-Briot (2019a), some interesting nuances, in comparison with the original analysis, occur. The results from the analysis without covariates stands, qualitatively, unaffected. In addition, in Table 6, the coefficients of the μ-equation, shows that, when there is not zero or full declaration, there is a negative and significant trend in declaration rate for the base and monitoring groups and a significant positive for the peer reporting group. For the base and monitoring group this effect is enhanced by Table 7 which shows that the probability for a zero declaration is increasing over time, for those groups. On the other hand, Table 8 shows that the effect is diminished by the fact that there is an upward trend in the probability of full declaration. For the peer reporting group the result is more unambigious. The positive trend is enhanced by a significant positive trend in the probability of full declaration.

Gross income has a significant negative effect on both the probability for zero and full declaration but not a significant effect on the observations in between.

The effect of an audit in the previous period is shown to affect the probability for zero declaration positively and and full declaration negatively. In the intermediate range, the effect on the declaration rate is negative. This is, thus, a clear indication of a negative effect of an audit in the previous period.

The age variable (a dummy for individuals above 31 years of age) affect the probability for zero declaration negatively and the probability for full declaration positively. For observations with neither zero nor full declaration the effect is not significant.

The tax morality variable is an answer, between 1 and 5, to the question whether "paying one's taxes is a social obligation" (Masclet, Montmarquette, and Viennot-Briot 2019a). Exactly how to use this variable; as a numerical, a dummy or some transformation, is not obvious. Here, this question will not be pursued and the variable will be used as a numerical variable which obtains values in the range 1 (strongly disagree) to 5 (strongly agree). The effect on the full declaration probability is, as expected, positive. As the value of the tax morality variable increases, so does the probability for full declaration. For the zero declaration probability the result is not significant (a p-value of 0.124) but, interestingly, also positive. The negative coefficient for the intermediate case shows the same thing, a decrease in declaration rate for an increase in the value of the tax morality variable. This coefficient is, however, not significant either (p-value of 0.092). Including cross-products of the tax morality variable and the treatment variable, not shown here, shed some partial light on this. The tax morality variable has, for the intermediate declarers, a significant negative impact for the base group and a non-significant effect for the other (zero and full declaration) groups. For the monitoring and peer reporting groups, the probability of zero declaration is negatively affected by the tax morality variable. For the base group, though, the effect is positive. The marginal effect of the full declaration probability, however, is however uniformly positive for all three treatments.

Table 6: μ-equation. The estimated effects of the treatments and the covariates for the intermediate declarers, see the γ-coefficients in (4).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	0.455	0.122	3.727	0.000
Peer reporting	0.385	0.090	4.277	0.000
Monitoring	0.240	0.083	2.877	0.004
Carbone	0.050	0.036	1.403	0.161
Period x Base	-0.016	0.005	-3.181	0.001
Period x Peer reporting	0.023	0.006	3.763	0.000
Period x Monitoring	-0.021	0.005	-4.095	0.000
Gross income	0.001	0.001	0.950	0.342
Audit_{t-1}	-0.102	0.044	-2.323	0.020
Risk Aversion	-0.260	0.036	-7.246	0.000
Age	0.080	0.053	1.507	0.132
Language	-0.186	0.041	-4.506	0.000
Female	0.388	0.036	10.779	0.000
Tax morality	-0.036	0.021	-1.683	0.092

Table 7: p_z-equation. The estimated effects of the treatments and the covariates for the null declarers, see the δ_z-coefficients in (6).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	-2.105	0.326	-6.461	0.000
Peer reporting	-1.497	0.427	-3.510	0.000
Monitoring	0.583	0.227	2.567	0.010
Carbone	0.086	0.095	0.911	0.363
Period x Base	0.043	0.014	3.009	0.003
Period x Peer reporting	0.051	0.030	1.697	0.090
Period x Monitoring	0.040	0.011	3.652	0.000
Gross income	-0.006	0.002	-2.749	0.006
Audit_{t-1}	0.557	0.109	5.107	0.000
Risk Aversion	0.206	0.097	2.123	0.034
Age	-0.926	0.190	-4.864	0.000
Language	0.024	0.116	0.208	0.836
Female	-1.059	0.105	-10.074	0.000
Tax morality	0.081	0.053	1.539	0.124

Table 8: p_o-equation. The estimated effects of the treatments and the covariates for the full declarers, see the δ_o-coefficients in (6).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	0.029	0.160	0.181	0.856
Peer reporting	0.483	0.117	4.119	0.000
Monitoring	-0.015	0.117	-0.128	0.898
Carbone	-0.058	0.047	-1.240	0.215
Period x Base	0.018	0.007	2.556	0.011
Period x Peer reporting	0.032	0.007	4.467	0.000
Period x Monitoring	0.012	0.007	1.638	0.102
Gross income	-0.017	0.001	-16.330	0.000
Audit_{t-1}	-0.095	0.057	-1.669	0.095
Risk Aversion	-0.323	0.048	-6.714	0.000
Age	0.181	0.069	2.611	0.009
Language	0.320	0.056	5.704	0.000
Female	-0.188	0.048	-3.929	0.000
Tax morality	0.227	0.027	8.271	0.000

4 Conclusion

In this paper the experimental data by Masclet, Montmarquette, and Viennot-Briot (2019a) has been revisited with the use of a zero-one inflated beta regression. The benefit of this method over the Tobit regression, used by those authors, is the way the zero and full declaration observations can be used in the analysis. The zero-one inflated beta regression has clear benefits when analyzing tax declaration rates. This is particularly true under the assumption that there is a difference in behaviour between individuals who optimize their declaration rates purely based on a financial outcome and those who insist on fully declare. Many results are in line with the original analysis, but there is one significant nuance that is revealed. The overall negative effect of monitoring on declaration rates is driven by zero-declaring observations. For observations with a fractional declaration rates, the effect is significantly positive. This results is robust to inclusion of random effects and the available covariates. Some additional interesting results from the analysis with covariate were also found. An increased gross income was shown to decrease both the probability for zero declaration and the probability for full declaration. Some results were more unambigous and entirely in line with Masclet, Montmarquette, and Viennot-Briot (2019a). They draw in the same direction for zero, intermediate and full declarers.

Appendix: Random effect model

Table 9: μ-equation. The estimated effects of the treatments for the intermediate declarers, see the γ-coefficients in (4).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	0.278	0.023	12.080	0.000
Peer reporting	0.764	0.036	21.123	0.000
Monitoring	0.104	0.033	3.199	0.001

Table 10: p_z-equation. The estimated effects of the treatments for the null declarers, see the δ_z-coefficients in (6).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	-2.800	0.099	-28.241	0.000
Peer reporting	-1.157	0.212	-5.459	0.000
Monitoring	1.208	0.127	9.515	0.000

Table 11: p_o-equation. The estimated effects of the treatments for the full declarers, see the δ_o-coefficients in (6).

	Estimate	Std. Error	t value	Pr(>|t|)
Base	0.150	0.047	3.184	0.001
Peer reporting	1.010	0.068	14.745	0.000
Monitoring	-0.042	0.067	-0.626	0.531

References

Allingham, Michael G, and Agnar Sandmo. 1972. "Income Tax Evasion: A Theoretical Analysis." *Journal of Public Economics* 1 (3-4): 323–38.

Alm, James. 2012. "Measuring, Explaining, and Controlling Tax Evasion: Lessons from Theory, Experiments, and Field Studies." *International Tax and Public Finance* 19 (1): 54–77.

Alm, James, and Antoine Malézieux. 2021. "40 Years of Tax Evasion Games: A Meta-Analysis." *Experimental Economics* 24 (3): 699–750.

Bérgolo, Marcelo L, Rodrigo Ceni, Guillermo Cruces, Matias Giaccobasso, and Ricardo Perez-Truglia. 2017. "Tax Audits as Scarecrows: Evidence from a Large-Scale Field Experiment." National Bureau of Economic Research.

Bjørneby, Marie, Annette Alstadsæter, and Kjetil Telle. 2021. "Limits to Third-Party Reporting: Evidence from a Randomized Field Experiment in Norway." *Journal of Public Economics* 203: 104512.

Bott, Kristina M, Alexander W Cappelen, Erik Ø Sørensen, and Bertil Tungodden. 2020. "You've Got Mail: A Randomized Field Experiment on Tax Evasion." *Management Science* 66 (7): 2801–19.

Gërxhani, Klarita, and Arthur Schram. 2006. "Tax Evasion and Income Source: A Comparative Experimental Study." *Journal of Economic Psychology* 27 (3): 402–22.

Malézieux, Antoine. 2018. "A Practical Guide to Setting up Your Tax Evasion Game."

Masclet, David, Claude Montmarquette, and Nathalie Viennot-Briot. 2019a. "Can Whistleblower Programs Reduce Tax Evasion? Experimental Evidence." *Journal of Behavioral and Experimental Economics* 83: 101459.

———. 2019b. "Data for: Can Whistleblower Programs Reduce Tax Evasion? Experimental Evidence." *Mendeley Data V1*, doi:10.17632/8hjw4nrhgm.1.

Ospina, Raydonal, and Silvia LP Ferrari. 2012. "A General Class of Zero-or-One Inflated Beta Regression Models." *Computational Statistics & Data Analysis* 56 (6): 1609–23.

Pickhardt, Michael, and Aloys Prinz. 2014. "Behavioral Dynamics of Tax Evasion–a Survey." *Journal of Economic Psychology* 40: 1–19.

Rigby, R. A., and D. M. Stasinopoulos. 2005. "Generalized Additive Models for Location, Scale and Shape,(with Discussion)." *Applied Statistics* 54.3: 507–54.