On the (Somewhat Puzzling) Relation Between Human Organ Donations and Tax Avoidance by U.S. Public Corporations

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Abstract: I examine four econometric issues related to a recent empirical finding that effective tax rates (ETRs) for U.S. corporations are positively related to state-level per-capita organ donations: (1) although the result comes from a firm-level ordinary least squares regression, it is equivalent to a state-level-mean regression estimated by weighted least squares (where the weights are the number of firms in each state), and absent this weighting there is no relation; (2) when annual regressions are estimated the positive relation is present in less than half the sample years and is clustered in the early 1990s; (3) when state dummy variables are added to control for state fixed effects there is no longer a relation; and (4) large coefficient changes resulting from weighting are consistent with model misspecification, suggesting that weighting may not be appropriate in this setting. I also show that the positive relation is associated with very high ETRs, which is inconsistent with a social capital explanation.

JEL classification: C20; C43; H25; H26

Key Words: social capital; tax avoidance; grouped data; weighted least squares

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"in an empirical attempt to verify the theory that storks bring babies, [a researcher] computed the correlation of the number of storks per 10000 women to the number of babies per 10000 women in a sample of counties. He found a highly statistically significant correlation and cautiously concluded that '... although there is no evidence of storks actually bringing babies, there is overwhelming evidence that, by some mysterious process, they influence the birth rate.'"

Kronmall (1993 p 379)

"Good empirical work in economics, on the other hand, is like realist fiction. Unlike fantasy, it claims to follow all the rules of the world (well… all the important ones). But of course it is fictional. That analogy is worth reflecting on, too."

McCloskey (1991 p 68)

1. Introduction

In a recent accounting study Hasan, Hoi, Wu and Zhang (2017) (HHWZ) report a somewhat surprising empirical finding: cash effective tax rates (Cash ETRs) for U.S. public corporations—a measure frequently used to identify tax avoidance—are positively related to annual per-capita human organ donations in the states in which the corporations are headquartered. Based on the theory of social capital, HHWZ conclude: "We find strong [...] associations between social capital and corporate tax avoidance, as captured by effective tax rates and book-tax differences. These results [...] are robust to using organ donation as an alternative social capital proxy" (p 629).

The HHWZ empirical result is remarkably robust, and the theory of social capital upon which they base their conclusions seems well accepted. My goal in this study is quite simple: to identify and discuss some potential econometric issues that stem from research design choices in HHWZ, and to illustrate how different design choices affect empirical results, and in turn the conclusions we draw.

This paper can be best viewed as having two parts. In the first part (Sections 2 through 4) I demonstrate three empirical results. First, the HHWZ research design, although using firm-level data and ordinary least squares (OLS) estimation, results in the same coefficient estimate as a state-level regression using mean values and weighted least squares (WLS) estimation, where the weights are the number of firms headquartered in a state. This result is well known in econometrics (see e.g., Solon, Haider and Wooldridge 2015, p 307) and reflects the fact that the independent variable (in this case per capita organ donations) is exactly the same for all observations in a state. Absent WLS weighting I find no positive relation between organ donations and ETRs. Second, using annual regressions (rather than a single regression pooled across time), the positive relation in the pooled 23-year sample period is present in less than half of the years in my sample, and is concentrated in the early 1990s. Third, when state dummy variables are added to the model to control for state fixed effects the positive relation between ETRs and organ donations goes away.

In the second part of the paper (Section 5) I examine the effect of WLS and weighting by the number of firms in a state. WLS is used in cases of grouped data with unequal group sizes to address the resulting heteroscedasticity,[1] and when appropriate it results in more efficient (although not more consistent) coefficient estimates. I argue that the large coefficient change due to weighting is consistent with model misspecification, and therefore weighting may not be appropriate for my sample. One misspecification I find is that the relation between ETRs and organ donations differs for states with low vs. high numbers of firms headquartered in the state: the relation is positive (negative) for states with high (low) numbers of firms.

[1] With grouped data and unequal group sizes, the variance of the group error term is inversely related to the number of observations in the group. Weighting by group size places more (less) emphasis on those groups with lower (higher) error term variance, leading to more efficient coefficient estimates.

I also investigate whether the positive relation for states with high numbers of firms is consistent with a social capital hypothesis, which predicts that those states with low (high) social capital will have higher (lower) levels of tax avoidance. The lowest level of tax avoidance (zero) should result in firms' ETRs being close to the US statutory rate. Based on this idea, I expect to find the positive relation between ETRs and organ donations driven by observations with low ETRs in states with low organ donations, whereas in states with high organ donations I expect to find ETRs close to the statutory rate. To test this conjecture I exclude from the sample two groups of observations: those with either very high or very low levels of both Cash ETRs and organ donations (highest and lowest 5% of observations, ranked by year). I find that the positive relation goes away when the observations with very high Cash ETRs and high organ donations are excluded. Because the high Cash ETRs associated with these excluded observations are so high (mean ETR = 87%; median ETR = 93%; seventy-fifth percentile ETR = 100%) this result seems inconsistent with a social capital explanation for the relation.

The results of my study make an important contribution to empirical accounting research by illustrating several underlying econometric issues that may impact research design choices for research questions that are similar to those of HHWZ. I clearly show that the positive relation between Cash ETRs and organ donations that I document is due to the use of WLS, that the result is concentrated in a small number of years in the sample period, and that the result goes away with the addition of state dummy variables to control for state fixed effects. I also discuss the appropriateness of the weighting used in the WLS estimation, and argue that the large change in the coefficient due to weighting may suggest the model is misspecified. Finally, I present evidence suggesting the positive relation in my sample is not necessarily consistent with a social capital explanation.

2. The relation between organ donations and ETRs

In this section I demonstrate the positive relation between Cash ETRs and per capita organ donations first reported by HHWZ. I don't replicate their result, because some of my control variables differ slightly from theirs,[2] I omit their five county-level control variables,[3] and my sample size is larger. However, like HHWZ I find a remarkably robust positive relation between organ donations and Cash ETRs. Because I do not replicate HHWZ's results, all of the econometric issues discussed in this study apply to my results rather than to HHWZ's.

Here is the complete regression model I use to estimate the relation between Cash ETRs and per-capita organ donations:

$$\begin{aligned} Cash\_ETR_{i,t} = \beta_0 &+ \beta_1 DONATE_{s,t} + \beta_2 SIZE_{i,t} + \beta_3 MB_{i,t} + \beta_4 LEV_{i,t} \\ &+ \beta_5 CH_{i,t} + \beta_6 CHGNOL_{i,t} + \beta_7 ROA_{i,t} + \beta_8 EQUITY_{i,t} + \beta_9 PPE_{i,t} \\ &+ \beta_{10} INTANG_{i,t} + \beta_{11} FI_{i,t} + \beta_{12} STTAX_{i,t} + \beta_{13} NOLDUM_{i,t} \\ &+ Industry\ Dummies + Year\ Dummies + e_{i,t} \end{aligned} \tag{1}$$

where the subscripts refer to firm i, year t, and state s. Note that all of the variables are firm-level (subscript i) except for DONATE, which is the same for all observations in the same state (subscript s). Variable definitions (also shown in Appendix A) with Compustat data codes in parentheses are as follows:

Cash_ETR = Cash taxes paid (TXPD) divided by pretax book income (PI) less special items (SPI). Observations without a positive denominator are eliminated. Cash ETRs greater than 1 (less than 0) are set to 1 (0);

[2] I measure market-to-book using assets rather than equity, to avoid the problem with very small or negative book value of equity. I use a continuous variable for percent of foreign income rather than a dummy variable. And I compute a state effective tax rate for each firm, rather than using a state-level statutory rate.

[3] The county-wide control variables I omit are income per capita, income inequality, dummy (urban), education, and age. HHWZ's Table 5 reports that only income inequality is significant at the 10% level.

DONATE = Per capita organ donations multiplied by 1,000. Following the description in HHWZ, per capita organ donations is the total number of organ donors in a state in a given year divided by total state population in that year;[4]

SIZE = Log of the market value of equity (PRCC_F × CSHO);

MB = Market-to-book ratio = market value of assets divided by book value of assets. Assets rather than equity is used to avoid the problem of firms with very small (or negative) book value of equity. Market value of assets is equal to market value of equity (PRCC_F × CSHO) plus book value of debt (AT – CEQ);

LEV = Leverage = long-term debt (DLTT) scaled by lagged assets (AT). Missing values are set to 0;

CH = Cash holding = cash and short term investments (CHE) divided by lagged assets (AT). Missing values are set to 0;

CHGNOL = Change in loss carry forward (TLCF), scaled by lagged assets (AT). Missing values are set to 0;

ROA = Return on assets = pretax income (PI) scaled by lagged assets (AT);

EQUITY = Equity income (ESUB) scaled by lagged assets (AT). Missing values are set to 0;

PPE = Property, plant, and equipment (PPENT) scaled by lagged assets (AT). Missing values are set to 0;

INTANG = Intangible assets (INTAN) scaled by lagged assets (AT). Missing values are set to 0;

[4] Organ donation data can be obtained from Organ Procurement and Transplantation Network (OPTN) via the link: https://optn.transplant.hrsa.gov/data/. Data on state populations is from the U.S. census bureau.

FI = Foreign income (PIFO) scaled by lagged assets (AT). Missing values are set to 0;

STTAX = State tax expense (TXS) divided by pretax book income (PI) less special items (SPI). Missing values are set to 0; and

NOLDUM = Dummy variable equal to 1 if the firm has a tax loss carryforward (TLCF) in the previous year, and 0 otherwise. Missing values for TLCF are set to 0.

Industry dummies represent Fama-French 12 industries. All continuous control variables are winsorized by year at 1% and 99% levels.

2.1 Sample

My sample follows that of HHWZ, and begins with all Compustat firms for the years 1990 through 2012. I eliminate observations with missing data for pretax income (PI), cash taxes paid (TXPD), assets (AT), stock price (PRCC_F), shares outstanding (CSHO), and book value of equity (CEQ). Other variables with missing data are set equal to zero. I also eliminate observations with negative pretax income, or a negative value for pretax income minus special items (SPI), the denominator of the Cash ETR. My final sample contains 66,143 firm-year observations over 23 years.

2.2 Results

Results of estimating equation (1) are reported in Column (1) of Table 1. The positive coefficient on DONATE of 0.770 (t-statistic = 2.89)[5] is consistent with the results in Table 5 of HHWZ of –0.205 (t-statistic = –1.84). Because HHWZ multiply the Cash ETR by –1 to convert it to a measure of tax avoidance, my positive coefficient is consistent with their negative

[5] All of the t-statistics reported in the tables are based on standard errors that have been clustered at the state level.

coefficient. Because I don't include all of the HHWZ control variables, and I measure some other control variables differently, my result is not a direct replication. Also, HHWZ eliminate more firms from their sample than I do, so their sample size is 55,415.[6] The difference in sample size and control variables is likely responsible for the difference in the size of the coefficient. I interpret my Table 1 results as being at least as strong, and perhaps stronger, than those reported by HHWZ. There is clearly a positive relation between Cash ETRs and per capita organ donations reflected in this regression.

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Insert Table 1

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2.3 Firm-level vs. state-level regressions

The first issue I address is related to a characteristic of the data used in HHWZ. When the X variable of interest in an OLS regression is exactly the same for all observations within a group (such as organ donations in a state), there is no covariance between the Y and X variables within the group, and the covariance captured by the regression coefficient is the covariance across groups.[7] In this case the regression coefficient is exactly the same if the Y variable for each *firm* is replaced with the mean of the Y variable for that firm's *group*. In the HHWZ study the independent variable of interest, per-capita organ donations, is a state-level variable that is exactly the same for all firms headquartered in a state. Because the independent variable is the same for all firms headquartered in the state, the coefficient estimate from an OLS regression will reflect the state-level means of the dependent variable, in this case Cash ETR. The

[6] HHWZ report that "the [donor] data for some states with smaller populations, such as Alaska, Delaware, Idaho, and New Hampshire, are missing," but I did not find this to be the case, so additional data may have been added to the donations database since HHWZ completed their analysis.

[7] Because the X variable is the same for all observations in the group, it is a constant for observations within the group. The covariance of a random variable (Y) with a constant is zero.

coefficient on organ donations will be exactly the same if the state-level mean Cash ETR is substituted for each firm's actual ETR. Appendix B provides a numerical example of this effect.

To investigate the effect of group means on regression coefficients, I need to compute a state-level mean Cash ETR for each state. However, all of the Cash ETR control variables are firm-level variables. To avoid losing the information in the firm-level control variables, I adopt a two-step procedure that I use for the balance of this study. In the first step I compute firm-level residual Cash ETRs by regressing Cash ETRs on all of the control variables (i.e., excluding DONATE) in Equation (1). Results from this regression model are shown in Column (2) of Table 1. Residuals from this regression (called Res_CETR) are used as the dependent variable in the remainder of the empirical tests in this study.

To estimate the relation between residual Cash ETRs and organ donations, in the second step I estimate the following regression model using individual firm-year observations:

$$Res\_CETR_{i,t} = \beta_0 + \beta_1 DONATE_{s,t} + Year\ Dummies + e_{i,t}. \quad (2)$$

Results are shown in Table 2, Panel A, Column (1). The coefficient on DONATE using the firm-level residual Cash ETR is 0.754 (t-statistic = 2.77), which is quite close to the estimate of 0.770 in Table 1.[8]

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Insert Table 2

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[8] The reason the coefficients are not exactly the same is that my approach is similar to, but not exactly the same as, the so-called "Frisch-Waugh-Lovell Theorem" (see Lovell 2008). To have identical coefficients, that theorem would require me to also obtain residuals for DONATE from a regression of DONATE on all of the control variables in (1). Because the control variables are firm-level, the residuals from such a regression would differ for firms headquartered in the same state. Because DONATE is a proxy for social capital, which is the same for all observations in a state, I don't regress DONATE on firm-level control variables. However, in the next section I regress DONATE on population, also a state-level variable, in the first step.

2.4 Using state-level means of residual Cash ETRs

To investigate the effect of replacing the individual Y values with the group-level mean of Y, I compute the mean residual Cash ETR (Mean_RCETR) for each state each year. I substitute this state-level mean for the firm-level residual Cash ETR, and re-estimate equation (2) using the state-level mean values. Note that this regression has exactly the same number of observations, and exactly the same values for DONATE, as the regression reported in Column (1). Results of re-estimating this regression using the state-level mean values of residual Cash ETRs are reported in Table 2, Panel A, Column (2).

The regression coefficient of 0.754 is exactly the same as that from the regression of the firm-level residual Cash ETRs reported in Column (1). This demonstrates the fact that the regression coefficient reflects the state-level mean of the residual Cash ETR rather than the individual firm-level ETRs. In other words, the regression coefficients are the same when all of the observations from the same state have exactly the same X variables, regardless of whether the Y variable is a firm-level or mean state-level amount.

Next I demonstrate how the coefficient would change if state-level regressions (rather than firm level regressions) were used, using the state-level mean values of the residual Cash ETRs. These results are reported in Panel B of Table 2. Note that the mean values of the dependent and independent variables for the state-level regressions in Panel B are exactly the same as those used in the firm-level regressions in Panel A, Column (2), but each state is represented just once each year rather than multiple times based on the number of firms in the state. The regression coefficient for the state-level OLS regression is 0.081 (t-statistic = 0.23). In other words, using mean values and one observation per state per year, there is no significant relation between mean residual Cash ETRs and organ donations. The large positive coefficient

in Panel A using firm-level observations reflects the fact that some states have more observations than other states.

Panel C of Table 2 demonstrates that the firm-level results are the same as the state-level mean results when weighted least squares is used in the estimation, and the weights are the number of firms in the state.[9] Using WLS the coefficient is 0.754, the same as for the firm-level results in Panel A. In other words, the positive relation between ETRs and organ donations is due to the fact that the state-level effects are weighted by the number of firms headquartered in the state that year, which differs from a low of n = 1 for states like Alaska, Montana and North Dakota, to a high of over 500 for California.

While WLS is often used in cases of grouped data, when the number of observations in each group is not the same, I discuss in Section 5 whether this weighting is appropriate for the model as specified in this study.

2.5 Specification of first-step model

To better specify the model in the first step, I make two important changes before proceeding with the rest of my analysis. First, it is clear from the above analysis that the number of firms in a state is a key factor in the results, and the number of firms is highly correlated with the population of the state (pearson correlation coefficient = 0.91). States with large populations, like New York, Texas, and California, also have a lot of corporations headquartered in the state, and the reverse is true for states with small populations.

[9] This result is known in the economics literature: see e.g., Angrist and Pische (2009 section 3.1.2). This same point is made in footnote 9 of Solon et al (2015), who state (for individual j in group i): "An important related point is that, if one has access to the individual-level data on y_{ij} and applies OLS to the regression of y_{ij} on X_i, this is numerically identical to the group-average WLS."

It turns out that both DONATE and Res_CETR are negatively correlated with state population. Here are the pearson correlation coefficients and p-values for the correlations of Res_CETR and DONATE with state population:

	Res_CETR	DONATE
correlation with population	-0.042	-0.151
p-value	<0.0001	<0.0001

Because both Res_CETR (the dependent variable) and DONATE (the independent variable) are negatively correlated with state population, population is a correlated omitted variable that could help explain the positive relation between Res_CETR and DONATE. Since population is also a state-level variable, I address this correlation by incorporating state population as a control variable in the first step of my research design by using the residuals (called Res_DON) from the following model as the independent variables in the second step:

$$DONATE_{s,t} = \beta_0 + \beta_1 MILPOP_{s,t} + e_{s,t}. \quad (3)$$

where MILPOP is the state's population in millions.

The second change I make has to do with the fact that the relation between ETRs and organ donations varies greatly across years, as will be demonstrated in the next section. Using year dummy variables may not adequately capture the year-specific relation between the variables. To allow the coefficients in the first-step regressions to differ across years, I estimate the first-step regressions annually, rather than using pooled regressions and year dummy variables.

To show how these two changes to the first-step regressions impact the second-step results, Table 3 presents the same second-step regressions as Table 2, but with the first-step variables (Res_CETR and Res_DON) estimated annually. Because both first-step models are

estimated annually, year dummy variables are omitted from the Table 3 second-step models. The coefficient in Table 3 is 0.291, which is less than half as large as that in Table 2. The Panel B result using state-level means and OLS show the coefficient is negative (–.004). In this case the use of WLS doesn't just cause a small positive coefficient to be more positive (as in Table 2); WLS flips the sign of the coefficient from negative to positive.

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Insert Table 3
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2.6 Does firm-level data improve the efficiency of the coefficient estimate?

Although I have shown that using grouped data (i.e., state-level means) and state-level regressions generates the same coefficients as using firm-level regressions and firm-specific residual ETRs when WLS is used, an argument can be made that information is lost when observations are grouped, and this leads to less efficient estimators. However, grouping of data does not cause a reduction in efficiency in my research setting, because the value of the independent variable (DONATE or Res_DON) is exactly the same for all members of a group (i.e., a state). Here is how Kmenta (1986, pp 369-370) explains why there is no loss of efficiency due to grouping in this case:[10]

> We know that by grouping the observations and estimating the regression coefficients from group means rather than from the individual observations, we are losing some information contained in the sample, namely, the information about the variation of the observations *within* each group. Therefore, we would

[10] Note that Kmenta's analysis assumes equal group sizes. In the case of my sample, the groups are not the same size, and this leads to heteroscedastic error terms and a loss of efficiency. The effect of heteroscedasticity and different group sizes is examined in Section 5.

expect that we would lose some efficiency in going from estimation based on all individual observations to estimation based on group means. We shall see whether, and to what extent, this is true by evaluating the ratio of $Var(\tilde{\beta})$ to $Var(\hat{\beta})$, where $\hat{\beta}$ denotes the least squares estimator of β based on individual observations.

The ratio of the two variables then is

$$\frac{Var(\tilde{\beta})}{Var(\hat{\beta})} = 1 + \frac{\sum_i \sum_g (X_{ig} - \bar{X}_g)^2}{\sum_g n_g (\bar{X}_g - \bar{X})^2} \tag{9.42}$$

This ratio is always greater than, or at best equal to, unity. The last term on the right-hand side measures the loss of efficiency resulting from the use of grouped data instead of individual observations. Note that the size of the numerator reflects the variation of the values of X *within* each group around the group mean, while the size of the denominator reflects the variation of the group means of X around the overall sample mean. Thus *we will lose no efficiency by grouping if there is no variation of the values of X within each group.* [...] there will always be some loss of efficiency by going from individual observations to groups *unless the X's within each group are all equal*. [emphasis added]

An alternative way to test for a loss of efficiency by grouping is suggested by Lang and Gottschalk (1996 p 558), who state: "If the X values within each group are similar, the two R-squares will be similar, and the loss in efficiency will be modest. If, on the other hand, replacing micro X values with group means removes a sizable portion of the variation in the Xs, the grouped regression will fit considerably better than the micro regression, and the loss in

efficiency will be larger. ... As long as R^2_m [for individual data] and R^2_{gr} [for grouped data] are small or are of roughly equal size, there is little loss from using grouped data. Stated alternatively, studies with a large number of persons per group may not add much to the precision of estimated parameters of group specific variables unless R^2_m is very different from R^2_{gr}." As the Table 3 results demonstrate, the R^2 for the firm-level regression (Table 3, Panel A, Column 1) of 0.000 is exactly the same as for the grouped state-level regression (Table 3, Panel B). This suggests there is no loss of efficiency by using the state-level regressions with mean values in this setting.

3. Annual results

All of the previous results are based on regressions that pool observations across time from 1990 through 2012, a sample period of 23 years. In this section I examine these results separately each year, using the same first-step research design as used in Table 3, but estimating annual regressions rather than pooled regressions for the second step. Table 4 presents three sets of results: Column (1) presents results using firm-level regressions and state-level means of Res_CETR, Column (2) presents state-level regressions estimated using OLS, and Column (3) presents state-level regressions estimated using WLS, where the weights are the number of firms in a state.

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Insert Table 4
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Several things are apparent from this table. First, it is clear that the coefficients for the firm-level regressions in Column (1) and the WLS state-level regressions in Column (3) are the same each year, confirming the results in the pooled regressions. Second, looking at the mean of

the annual coefficients, it is clear that the mean coefficient is positive (0.461) using firm-level regressions or WLS state-level regressions, but is negative (–0.100) using state-level regressions estimated with OLS. This result is also consistent with the results in pooled regressions in Table 3.

Perhaps the most surprising thing about these annual results is the fact that, even for the firm-level regressions (or WLS state-level regressions), the positive coefficient on organ donations is not found uniformly over the sample period, but appears to be concentrated in the period 1990 through 1996, as well as in 2002 and 2003. Considering only years with a positive t-statistic greater than 1.00, only 8 out of the 23 years in the sample period exhibit a positive relation between Cash ETRs and organ donations, and 6 of the 8 are prior to 1997.

While these annual results do not suggest that the pooled result is not present, they do suggest that the effect being captured in the pooled regression is not consistent over time, and is concentrated in one part of the sample period.

4. Including state dummy variables

HHWZ include 0/1 dummy variables in their model to control for year and industry fixed effects, but not for state fixed effects. At first glance, this may seem appropriate in this setting, as each state's per capita organ donations (relative to other states) might be relatively constant over time. Social capital in a state may not vary a great deal over time, and if organ donations is a good proxy for social capital, perhaps adding state dummies would simply remove the very effect the regression is trying to identify.

To see whether this is the case, I examine the variation in states' relative per capita organ donations over time. For each year in the sample period I rank states based on per capita organ

donations, and sort the states into deciles based on their rank, with decile scores from 0 to 9. For each state I then compute mean, minimum, maximum, and standard deviation of these ranks over the 23-year sample period. The results are presented in Table 5.

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Insert Table 5
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The Table 5 descriptive statistics show that 46 of the states had a minimum rank of 0, 1, or 2 during the sample period. Of these 46 states, 35 had a maximum rank of 7, 8, or 9 during the same sample period. Viewed differently, 40 of the states had a maximum rank of 7, 8, or 9 during the sample period. Of these 40 states, 35 had a minimum rank of 0, 1, or 2 during the same sample period. The mean of the standard deviations for all the states is 2.03. These descriptive statistics suggest that there is quite a lot of variation in the relative per capita donations across the states over the sample period. States may be relatively high in some years, and low in other years. Therefore, using state dummy variables to capture state fixed effects seems appropriate, since the relative organ donations themselves do not appear to be constant over time.

Table 6 shows the effect of adding state dummy variables to the Table 1 firm-level regression model. With state dummies added, the coefficient on DONATE drops from 0.770 to 0.078 (approximately one-tenth as large), and the t-statistic is 0.27. In other words, adding state dummy variables to capture state fixed effects causes the relation between Cash ETRs and organ donations shown in Table 1 to become small and not significantly different from zero.

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Insert Table 6
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5. Weighting and WLS

5.1 General discussion of weighting

In this section I return to the result demonstrated in Section 2: that the positive relation between ETRs and organ donations only results when the regression is weighted by the number of firms in a state, either by estimating a firm-level regression, or by using WLS for a state-level regression. In this section I explore whether such weighting is appropriate for this particular model and data.

Solon et al. (2015 p 301) make the observation: "In published research, top-notch empirical scholars make conflicting choices about whether and how to weight, and often provide little or no rationale for their choices. And in private discussions, we have found that accomplished researchers sometimes own up to confusion or declare demonstrably faulty reasons for their weighting choices."

While my interest in this paper is on the coefficient estimate, the papers in the economics and statistics literature dealing with weighting focus almost exclusively on the effect on estimates of standard errors (e.g., Donald and Lang 2007; Wooldridge 2003). However, weighting can also affect the coefficient estimates, as demonstrated in Tables 2 and 3. In addressing this point, Solon et al. (2015, p 308) make the following suggestion:

> ... it often is good practice to report both weighted and unweighted estimates. [...] Under exogenous sampling and correct specification of the conditional mean [...], both OLS and WLS are consistent for estimating the regression coefficients. On the other hand, under either the endogenous sampling discussed in the next section or model misspecification [...], OLS and WLS generally have different

> probability limits. Therefore, as suggested by DuMouchel and Duncan (1983), *the contrast between OLS and WLS estimates can be used as a diagnostic for model misspecification* or endogenous sampling. In truth, of course, the parametric models we use for estimating causal effects are nearly always misspecified at least somewhat. Thus, the practical question is not whether a chosen specification is exactly the true data-generating process but rather whether it is a good enough approximation to enable nearly unbiased and consistent estimation of the causal effects of interest. *When weighted and unweighted estimates contradict each other, this may be a red flag that the specification is not a good enough approximation to the true form of the conditional mean.* [emphasis added]

Angrist and Pischke (2009 section 3.4.1) state that: "Weights can be used in a number of ways, and how they are used may well matter for your results. Regrettably, however, the case for or against weighting is often less than clear-cut." They go on to state: "if your goal is to get back to the microdata regression, it makes sense to weight by group size."[11] Romano and Wolf (2017 p 2) caution that: "Any efficiency gain from weighting is likely to be modest, and incorrectly or poorly estimated weights can do more harm than good."

Why weight the observations at all? Solon et al. (2015, p 301) "discuss three distinct potential motives for weighting when estimating causal effects: (1) to achieve precise estimates by correcting for heteroscedasticity; (2) to achieve consistent estimates by correcting for endogenous sampling; and (3) to identify average partial effects in the presence of unmodeled

[11] Angrist and Pische (2009 section 3.4.1) add this aside: "We note, however, that macroeconomists, accustomed to working with published averages and ignoring the underlying microdata, might disagree, or perhaps take the point in principle but remain disinclined to buck tradition in their discipline, which favors the unweighted analysis of aggregates."

heterogeneity of effects. In each case, we find that the motive sometimes does not apply in situations where practitioners often assume it does." An additional reason for weighting is suggested by Shalizi (2009), who refers to it as "focusing accuracy," which is explained as follows: "We may care very strongly about predicting the response for certain values of the input – ones we expect to see often again, ones where mistakes are especially costly or embarrassing or painful, etc. – than others. If we give the points x_i near that region big weights w_i, and points elsewhere smaller weights, the regression will be pulled towards matching the data in that region."

Of the above reasons for weighting, the only one applicable in my setting is the first: to achieve efficient estimates in the presence of heteroscedasticity, where the heteroscedasticity is due to grouping when the number of observations in each group is not the same. I address this in the following section.[12,13]

5.2 Weighting to correct heteroscedasticity

In this section I investigate the effect of weighting by number of firms to solve a problem of heteroscedasticity in my data. Solon et al (2015 p 304) explain: "One motivation for weighting, taught for decades in undergraduate and graduate econometrics classes, is to correct for heteroskedastic error terms and thereby achieve more precise estimation of coefficients in linear or nonlinear regression models of causal effects."

[12] If selecting corporations from Compustat can be viewed as drawing observations from groups (i.e., states), then the probability of a corporation from a particular state being included in the sample differs across the states. Viewed this way, the regressions being examined in this study may suffer from the problem of endogenous sampling, and weighting by the inverse of the probability of selection is the correct solution. If the number of firms is proportional to the probability of selection, then the *inverse* of the number of firms would be the correct weight.

[13] Another potential argument for weighting by number of firms is that more firms in a state allows a more accurate estimate of that state's true underlying mean ETR. To test this idea, I compute the variance of the dependent variable Res_CETR for each state over the sample period. The variance is not smaller for states with more firms.

There is a "classic heteroskedasticity-based argument for weighting when the dependent variable is a group average and the averages for different groups are based on widely varying within-group sample sizes" because "as taught in almost every introductory econometrics course, OLS estimation ... is inefficient and also leads to inconsistent standard errors if nothing is done to correct the standard errors for heteroskedasticity. The WLS estimator that applies least squares to the reweighted equation ... is the minimum-variance linear unbiased estimator and also generates consistent standard errors" (Solon et al. 2015 p 305). Table 7 reports descriptive statistics on the number of firms in each state each year. If my regression results reflect grouped data, then clearly the number of observations differs dramatically across the groups.

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Insert Table 7

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The idea behind weighting in this situation is that the variance of the regression residuals is smaller for groups with more observations, and putting more weight on the groups with smaller residual variances results in more efficient coefficient estimates. However, although the WLS coefficient estimates are more efficient (having a lower variance than OLS estimates), the OLS coefficients are still consistent in that the OLS and WLS coefficients should, on average, be the same. This is why the suggestion has been made (Solon et al. 2015) that large differences in WLS and OLS coefficients could be a "red flag" that the underlying model is misspecified.

Since there are large differences in the WLS and OLS coefficients in my model (as shown in Table 3: 0.291 vs –0.004), it raises the question: what could be the misspecification? One possibility is that the relation between Cash ETRs and organ donations could differ for states with large and small numbers of firms. Pooling all states together forces the regression coefficient to be the same across the two types of states, which may not reflect the underlying

economic relations. To test this idea, I rank all of the states each year by the number of firms in the state that year, and I code each state as having more ("high") or less ("low") firms than the median number of firms in a state for the year. I then re-estimate the model in Table 3 Panel B (the state-level model estimated using OLS) separately for the two types of states. Results are presented in Table 8.

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Insert Table 8
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Panel A of Table 8 reproduces the results from Table 3 Panel B for comparison. Panel B (Panel C) of Table 8 reports results for the sample containing the states with the lowest (highest) number of firms. Because the states with a large number of firms have many more firm-level observations than the states with a small number of firms, the sample size for the Panel C results reflects many more individual firm-year observations than the sample size for the Panel B results. However, these regressions are at the state level, and each Panel reflects approximately the same number of states.

As the Panel B results (for states with the smallest number of firms) demonstrate, the coefficient on Res_DON is negative (–0.380), whereas in Panel C (for states with the largest number of firms) the coefficient is positive (0.300), although neither coefficient is significantly different from zero. These results suggest that one source of misspecification in my model could be the restriction that the relation between ETRs and organ donations is the same for firms with both small and large numbers of firms.

To provide further evidence on the impact of the number of firms on the coefficient, I re-estimate the regression model from Table 1 after first separating the sample into two parts: those states with the smallest and largest number of firms each year. Note that because the Table 1

regression is a firm-level regression, the number of observations will be much larger for the states with the largest number of firms, although approximately the same number of states are represented in each regression. These results are presented in Table 9.

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Insert Table 9
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As the Table 9 results demonstrate, the coefficient on DONATE is negative (–0.301) and not significant for the states with the smallest number of firms, whereas it is positive (0.914) and significant (t-statistic = 3.23) for the states with the largest number of firms. These results are consistent with those reported in Table 8, and suggest that the relation between ETRs and organ donations is different in the two types of states.

Because the relation between ETRs and organ donations is different for states with smaller and larger number of firms, weighting the regression by the number of firms to address heteroscedastic OLS residuals will result in the coefficient changing, as is apparent in Table 3. Thus a possible misspecification of the underlying model can result in different coefficients under OLS and WLS, as suggested by Solon et al. 2015.

5.3 Revisiting the social capital hypothesis

In this section I focus just on the sample from states with a large number of firms (where the relation between ETRs and organ donations is positive) to see whether the result for those states is consistent with the social capital hypothesis suggested by HHWZ. My interpretation of the social capital explanation is that those firms in states with high social capital will tend not to engage in tax avoidance, and thus I expect the ETRs for these firms to be close to the statutory U.S. corporate tax rate. This view of social capital and tax avoidance suggests that any positive

relation between ETRs and organ donations should be driven by firms in states with low social capital engaging in more tax avoidance, and thus reducing their ETRs to low levels.

In other words, I expect that if the social capital explanation is descriptive of the relation in the data, if I remove observations with very low ETRs and very low donations, the positive relation should go away or be very much reduced. On the other hand, if I remove observations with very high ETRs and very high donations, this should not have a large impact on the positive relation.

I investigate this conjecture by starting with the sample of states with a large number of firms (the observations exhibiting the positive relation between ETRs and donations), and then for each year ranking each firm-level observation on both Res_CETR (the dependent variable) and Res_DON (the independent variable) each year in the sample period. I code an observation as H (L) if it is in the highest (lowest) 5% of all observations for the year for that variable. I then remove (1) all firm-level observations coded H for *both* Res_CETR and Res_DON (H/H observations), and (2) all firm-level observations coded L for *both* Res_CETR and Res_DON (L/L observations). I then re-estimate the regression from Panel C of Table 8 after deleting these H/H and L/L observations. Because this is a state-level regression, the number of observations (i.e., states) remains the same, even though the number of individual firm-year observations that make up the state-level mean observations has been decreased. Results of re-estimating this regression are reported in Table 10 Panel A.

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Insert Table 10

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The coefficient after removing the H/H and L/L observations is negative (–0.374), which suggests that the observations that are removed were associated with the positive relation

between ETRs and organ donations reflected in Table 8, where the coefficient was positive (0.300). The effect of removing only the H/H observations is reported in Panel B of Table 10. These are observations for firms with the very highest ETRs (Res_CETR) and the very highest organ donations (Res_DON) each year. Removing just these H/H observations (and leaving the L/L observations) results in a negative coefficient (–0.159), suggesting that these H/H observations are associated with the positive relation between ETRs and organ donations in the overall sample.

The effect of removing only the L/L observations is reported in Panel C of Table 10. These are observations for firms with the very lowest ETRs (Res_CETR) and the very lowest organ donations (Res_DON) each year. Removing just these L/L observations (and leaving the H/H observations) results in a positive coefficient (0.085), suggesting that these L/L observations are *not* causing the positive relation between ETRs and organ donations in the overall sample (although they do appear to make the positive relation larger).

I interpret the results reported in Table 10 as inconsistent with the social capital hypothesis in explaining the positive relation between ETRs and organ donations found for states with high numbers of firms. The positive relation appears to be more associated with firms that have very high ETRs (mean ETR = 87%; median ETR = 93%; seventy-fifth percentile ETR = 100%). While social capital theory may suggest that managers of firms located in high social capital states will voluntarily limit the amount of tax avoidance, to the best of my knowledge the theory does not suggest these managers would voluntarily pay rates of tax that are this high.

6. Conclusion

My purpose in this study is to point out and investigate some econometric issues that arise from a research design that regresses firm-level data on an explanatory variable that is exactly the same for all observations in a state. Issues arise because some states have only 1 or 2 observations per year, whereas other states have several hundred observations, thus raising the question of weighting the regression. A simple OLS regression using firm-level data gives the same result as a state-level regression using state-level mean variables, and estimated using weighted least squares.

I use a sample and research design that is similar to that of a prior published study (HHWZ) to first demonstrate a robust positive relation between organ donations and corporation ETRs. I then use this data to investigate whether weighting is appropriate in this setting, and what the effect of weighting is on the coefficient estimate. I also investigate the behavior of the regression coefficient over the sample period, and find that the positive relation is present in less than half the sample years, and is concentrated in the early 1990s. Finally, I demonstrate that the positive relation goes away when state dummy variables are added to the model to control for state fixed effects.

I emphasize that the empirical results I present, and the conclusions I draw from them, are solely reflective of the data that I use and the regressions that I run. I make no attempt to obtain HHWZ's exact sample or replicate their results exactly, and I use a somewhat different two-step regression approach. Therefore, my findings should not be interpreted as suggesting that the results reported in HHWZ are incorrect, and I make no such claim.

Appendix A: Variables Definitions

Dependent variables

Cash_ETR	Cash taxes paid (TXPD) divided by pretax book income (PI) less special items (SPI). Observations without a positive denominator are eliminated. Cash ETRs greater than 1 are set to 1 and Cash ETRs less than 0 are set to 0. This is a firm-level variable.
Res_CETR	Residuals from regression of Cash ETR on the set of control variables and industry dummy variables. These are annual regressions (except for Tables 1 and 2 when year dummy variables are used). This is a firm-level variable.
Mean_RCETR	Mean of the Res_CETR values for all of the firms with headquarters in a particular state for the year. This is a state-level variable.

Independent variables

DONATE	Per capita organ donations multiplied by 1,000. Following the description in HHWZ, per capita organ donations is the total number of organ donors in a state in a given year divided by total state population in that year. Data on state populations is from the U.S. census bureau. Organ donation data can be obtained from Organ Procurement and Transplantation Network (OPTN) via the link: https://optn.transplant.hrsa.gov/data/. This is a state-level variable.
Res_DON	Residual from annual regressions of DONATE on total state population (in millions). This is a state-level variable.

Control variables (all firm-level)

SIZE	Log of the market value of equity (PRCC_F × CSHO).
MB	Market-to-book ratio = market value of assets divided by book value of assets. Assets rather than equity is used to avoid the problem of firms with very small (or negative) book value of equity. Market value of assets is equal to market value of equity (PRCC_F × CSHO) plus book value of debt (AT – CEQ).
LEV	Leverage = long-term debt (DLTT) scaled by lagged assets (AT). Missing values are set to 0.
CH	Cash holding = cash and short term investments (CHE) divided by lagged assets (AT). Missing values are set to 0.
CHGNOL	Change in loss carry forward (TLCF), scaled by lagged assets (AT). Missing values are set to 0.
ROA	Return on assets = pretax income (PI) scaled by lagged assets (AT).
EQUITY	Equity income (ESUB) scaled by lagged assets (AT). Missing values are set to 0.

Appendix A (continued)

PPE	Property, plant, and equipment (PPENT) scaled by lagged assets (AT). Missing values are set to 0.
INTANG	Intangible assets (INTAN) scaled by lagged assets (AT). Missing values are set to 0.
FI	Foreign income (PIFO) scaled by lagged assets (AT). Missing values are set to 0.
STTAX	State tax expense (TXS) divided by pretax book income (PI) less special items (SPI). Missing values are set to 0.
NOLDUM	Dummy variable equal to 1 if the firm has a tax loss carryforward (TLCF) in the previous year, and 0 otherwise. Missing values for TLCF are set to 0.

All continuous control variables are winsorised by year at the 1% and 99% levels

Appendix B: Numerical Example

This appendix uses a simple numerical example to illustrate what happens with a firm-level OLS regression in which the independent variable is the same for all members of a group. There are two effects illustrated. First, the estimated coefficient is the same if the within-group mean of the dependent variable is substituted for the actual value of the dependent variable.

Assume there are 9 pairs of Y,X observations, divided into 3 groups, and that the value of X is the same within each group. Example A below, with 3 observations in each X group, shows how the regression coefficient is unaffected if the within-group mean of Y is substituted for the individual Y values.

Example A: Equal number of observations in each X group

X group mean Y	Y	X	Y	X
	0.24	0.4	0.22	0.4
	0.22	0.4	0.22	0.4
0.22	0.20	0.4	0.22	0.4
	0.04	0.3	0.02	0.3
	0.02	0.3	0.02	0.3
0.02	0.00	0.3	0.02	0.3
	0.16	0.2	0.18	0.2
	0.18	0.2	0.18	0.2
0.18	0.20	0.2	0.18	0.2
regression coef.		0.200		0.200

The second effect is that the coefficient can differ if the number of observations in each group is not the same. This is the same coefficient that would be obtained if a group-level

regression was estimated, using the group mean values, and the estimation was done using weighted least squares, where the weights are the number of observations in each group. [14]

Example B below uses the same Y and X values to show that the regression coefficient differs from those of Example A when the number of observations in each X group is not the same (7 in one group and 1 each in the other two groups).

Example B: Different number of observations in each X group

X group mean Y	Y	X	Y	X
	0.24	0.4	0.22	0.4
	0.22	0.4	0.22	0.4
	0.20	0.4	0.22	0.4
	0.24	0.4	0.22	0.4
	0.22	0.4	0.22	0.4
	0.20	0.4	0.22	0.4
0.22	0.22	0.4	0.22	0.4
0.02	0.02	0.3	0.02	0.3
0.18	0.18	0.2	0.18	0.2
regression coef.		0.500		0.500

Comparing the right hand columns in Examples A and B above, it is clear that the Y,X pairs are exactly the same in the two examples—(0.22,0.4), (0.02,0.3) and (0.18,0.2)—and that the only difference is the number of observations in each group.

[14] See Solon et al. (2015, footnote 9)

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Table 1
Reproduction of relation in Table 5 of HHWZ
and estimation of residual Cash_ETR

	(1)		(2)	
	Reproduction of relation in Table 5 of HHWZ		Estimation of residual Cash_ETR	
Variable	Coef.	t-stat.	Coef.	t-stat.
Intercept	0.314	25.50	0.333	35.93
DONATE	**0.770**	**2.89**	-	-
SIZE	0.000	0.35	0.000	0.38
MB	-0.010	-6.49	-0.010	-6.32
LEV	-0.064	-14.41	-0.064	-14.35
CH	-0.028	-5.18	-0.028	-5.05
CHGNOL	0.165	11.44	0.166	11.38
ROA	-0.076	-4.95	-0.075	-4.78
EQUITY	-1.015	-4.14	-1.020	-4.09
PPE	-0.039	-4.25	-0.039	-4.21
INTANG	0.001	0.94	0.001	0.97
FI	0.214	2.14	0.206	2.02
STTAX	1.489	43.28	1.487	42.47
NOLDUM	-0.055	-18.57	-0.055	-18.67
year dummies	yes		yes	
ind. dummies	yes		yes	
r-squared	0.166		0.166	
n=	66,143		66,143	

Dependent variable is Cash_ETR.
Variables are defined in Appendix A.
t-statistics computed using standard errors clustered at the state level.

Table 2
Regressions using residual Cash_ETR from Table 1 regression

	Dependent variable:			
	(1)		(2)	
	Residual ETR from Table 1 regression		State-level mean of residual ETR	
Variable	Coef.	t-stat.	Coef.	t-stat.
Panel A: Firm-year observations (n=66,143)				
Intercept	-0.019	-2.13	-0.019	-2.13
DONATE	**0.754**	**2.77**	**0.754**	**2.77**
year dummies	yes		yes	
r-squared	0.001		0.027	
Panel B: State-year observations using OLS (n=1,144)				
Intercept	-	-	-0.008	-0.55
DONATE	-	-	**0.081**	**0.23**
year dummies			yes	
r-squared			0.018	
Panel C: State-year observations using WLS (n=1,144)				
Intercept	-	-	-0.019	-2.11
DONATE	-	-	**0.754**	**2.74**
year dummies			yes	
r-squared			0.027	

Dependent variable in column (1) is Res_CETR, residual from Table 1 regression.
Dependent variable in column (2) is Mean_RCETR, state level mean of Res_CETR.
WLS weights observations by number of firms in the state each year.
Variables are defined in Appendix A.
t-statistics computed using standard errors clustered at the state level.

Table 3
Regressions using residual Cash_ETR from Table 1 regression
Residuals are from annual regressions

	Dependent variable:			
	(1)		(2)	
	Residual ETR from Table 1 regression		State-level mean of residual ETR	
Variable	Coef.	t-stat.	Coef.	t-stat.
Panel A: Firm-year observations (n=66,143)				
Intercept	-0.000	-0.00	-0.000	-0.00
Res_DON	**0.291**	**1.06**	**0.291**	**1.06**
r-squared	0.000		0.004	
Panel B: State-year observations using OLS (n=1,144)				
Intercept	-	-	0.008	2.48
Res_DON	-	-	**-0.004**	**-0.01**
r-squared			0.000	
Panel C: State-year observations using WLS (n=1,144)				
Intercept	-	-	-0.000	-0.00
Res_DON	-	-	**0.291**	**1.06**
r-squared			0.004	

Dependent variable in column (1) is Res_CETR, residual from Table 1 regression, estimated annually without year dummies.
Dependent variable in column (2) is Mean_RCETR, state level mean of Res_CETR.
Res_DON is residual from regression of DONATE on population (in millions), estimated annually without year dummies.
WLS weights observations by number of firms in the state each year.
Variables are defined in Appendix A.
t-statistics computed using standard errors clustered at the state level.

Table 4
Annual regressions

grouping estimation	(1) firm-level OLS		(2) state-level OLS		(3) state-level WLS	
	coef	t-stat	coef	t-stat	coef	t-stat
1990	2.150	1.88	(0.584)	(0.40)	2.150	1.98
1991	2.128	2.83	0.568	0.48	2.128	2.60
1992	1.992	3.53	1.205	0.95	1.992	3.57
1993	1.451	2.56	1.433	1.58	1.451	2.19
1994	0.920	1.46	(1.057)	(0.84)	0.920	1.31
1995	0.442	0.53	(4.092)	(2.91)	0.442	0.46
1996	1.058	1.40	(0.358)	(0.48)	1.058	1.54
1997	0.456	0.48	(1.521)	(1.41)	0.456	0.55
1998	(0.049)	(0.08)	(1.227)	(1.21)	(0.049)	(0.06)
1999	(0.541)	(0.89)	(0.031)	(0.03)	(0.541)	(0.75)
2000	(0.521)	(0.90)	(0.106)	(0.07)	(0.521)	(0.62)
2001	(0.340)	(0.39)	1.177	0.88	(0.340)	(0.42)
2002	1.820	4.44	1.117	0.74	1.820	2.88
2003	0.961	2.24	(0.461)	(0.47)	0.961	1.53
2004	0.072	0.17	(0.911)	(0.96)	0.072	0.14
2005	0.323	0.82	0.256	0.30	0.323	0.67
2006	(0.634)	(1.48)	(0.460)	(0.78)	(0.634)	(1.29)
2007	(0.664)	(1.15)	(0.212)	(0.19)	(0.664)	(1.04)
2008	(0.267)	(0.46)	(0.529)	(0.57)	(0.267)	(0.42)
2009	(0.693)	(1.22)	0.403	0.22	(0.693)	(1.02)
2010	(0.073)	(0.11)	0.541	0.58	(0.073)	(0.10)
2011	0.204	0.29	1.004	1.00	0.204	0.28
2012	0.410	0.90	1.544	1.98	0.410	0.81
mean	0.461	0.732	(0.100)	(0.069)	0.461	0.643

Dependent variable is Mean_RCETR, state level mean of Res_CETR.
Res_CETR is residual from Table 1 regression, estimated annually without year dummies.
Independent variable is Res_DON, residual from regression of DONATE on population (in millions), estimated annually without year dummies.
WLS weights observations by number of firms in the state each year.
Variables are defined in Appendix A.
t-statistics for model (1) computed using standard errors clustered at the state level.

Table 5
Descriptive statistics for ranks of DONATE by state from 1990 through 2012
States are ranked each year and formed into deciles with scores from 0 to 9

state	mean	std dev	min	max
AK	6.43	3.23	0	9
AL	5.96	1.80	2	8
AR	3.78	2.59	0	8
AZ	2.52	1.83	0	7
CA	1.91	0.79	1	3
CO	3.35	2.23	0	7
CT	2.00	1.83	0	6
DC	7.96	2.14	0	9
DE	7.52	2.21	0	9
FL	3.39	2.06	0	7
GA	2.65	1.23	1	5
HI	1.00	1.71	0	7
IA	4.83	2.15	1	8
ID	3.35	2.84	0	8
IL	6.43	1.20	4	9
IN	3.74	2.28	0	8
KS	4.13	2.42	0	8
KY	2.74	2.18	0	7
LA	4.52	2.13	1	8
MA	3.70	1.36	1	6
MD	7.70	1.66	2	9
ME	4.39	2.33	0	8
MI	7.09	1.04	5	9
MN	8.70	0.56	7	9
MO	5.22	1.83	0	7
MS	1.70	1.77	0	6
MT	5.52	3.00	0	9
NC	2.78	1.17	1	5
ND	7.09	2.02	2	9
NE	4.26	2.45	0	8
NH	4.13	2.75	0	9
NJ	4.22	2.80	0	8
NM	3.61	2.71	0	8
NV	3.43	2.19	0	9
NY	3.00	1.95	0	6
OH	5.87	1.25	3	8

Table 5 (continued)

OK	2.09	1.98	0	6
OR	2.35	2.21	0	6
PA	7.30	1.87	2	9
RI	3.74	3.17	0	8
SC	4.26	2.56	0	9
SD	6.13	2.69	0	9
TN	4.70	2.10	1	9
TX	2.96	1.43	1	6
UT	6.30	2.01	2	9
VA	5.26	1.79	1	8
VT	5.78	2.81	0	9
WA	0.87	0.97	0	3
WI	8.43	0.73	7	9
WV	4.96	2.46	0	9
WY	4.26	3.25	0	9

DONATE is defined in Appendix A.

Table 6
Effect of state dummy variables on Table 1 results

	(1)		(2)	
	Table 1 results reproduced		Table 1 results with state dummy variables	
Variable	Coef.	t-stat.	Coef.	t-stat.
Intercept	0.314	25.50	0.381	24.83
DONATE	**0.770**	**2.89**	**0.078**	**0.27**
SIZE	0.000	0.35	-0.015	-4.62
MB	-0.010	-6.49	-0.010	-8.54
LEV	-0.064	-14.41	-0.064	-15.13
CH	-0.028	-5.18	-0.023	-4.23
CHGNOL	0.165	11.44	0.164	12.43
ROA	-0.076	-4.95	-0.082	-5.39
EQUITY	-1.015	-4.14	-0.983	-4.03
PPE	-0.039	-4.25	-0.044	-5.01
INTANG	0.001	0.94	0.001	1.00
FI	0.214	2.14	0.260	2.89
STTAX	1.489	43.28	1.529	45.62
NOLDUM	-0.055	-18.57	-0.054	-18.63
year dummies	yes		yes	
ind. dummies	yes		yes	
state dummies	no		yes	
r-squared	0.166		0.166	
n=	66,143		66,143	

Dependent variable is Cash_ETR.
Variables are defined in Appendix A.
t-statistics computed using standard errors clustered at the state level.

Table 7
Descriptive statistics on number of sample firms headquartered in a state each year

	number of firms in a year			
state	mean	std. dev.	min	max
AK	1.6	1.0	1	4
AL	22.3	6.3	13	34
AR	14.8	2.6	11	21
AZ	39.0	11.2	23	63
CA	381.0	72.9	290	545
CO	54.3	9.9	40	78
CT	71.9	16.8	48	103
DC	7.6	1.5	6	12
DE	13.0	3.2	7	18
FL	126.1	29.3	80	182
GA	77.4	18.2	49	107
HI	5.1	1.5	3	7
IA	21.7	5.5	12	32
ID	5.6	1.9	3	11
IL	139.8	28.1	95	191
IN	46.5	11.0	29	66
KS	17.3	2.8	12	22
KY	23.7	3.9	16	31
LA	18.3	4.3	10	25
MA	132.5	28.6	88	190
MD	45.3	8.5	33	60
ME	6.2	2.1	2	9
MI	62.5	16.5	38	89
MN	86.8	19.9	59	123
MO	57.1	8.9	41	73
MS	7.3	2.5	3	11
MT	2.4	1.0	1	4
NC	62.7	13.0	44	84
ND	2.0	0.8	1	3
NE	14.0	2.8	8	20
NH	14.2	5.7	4	24
NJ	128.5	24.7	90	172
NM	3.3	1.7	1	6
NV	22.0	5.1	13	33
NY	261.9	38.6	203	335

Table 7 (continued)

OH	118.7	26.4	77	159
OK	24.7	4.1	14	32
OR	28.4	8.4	13	45
PA	135.6	21.7	100	172
RI	10.6	2.8	7	16
SC	19.3	5.7	10	30
SD	5.2	1.8	2	8
TN	47.6	9.2	35	66
TX	279.5	49.0	215	384
UT	22.8	5.7	13	35
VA	85.4	14.4	61	109
VT	5.2	1.8	2	8
WA	40.8	11.2	24	69
WI	53.1	12.1	32	73
WV	4.1	2.4	1	9
WY	2.0	0.0	2	2

Table 8
Effect of different number of firms in a state on coefficient estimate

Variable	Dependent variable is state-level mean of residual ETR: Mean_RCETR	
	Coefficient	t-statistic
Panel A: All observations (n=1,144)		
Intercept	0.008	3.99
Res_DON	**-0.004**	**-0.02**
r-squared	0.000	
Panel B: States with smallest number of firms (n=568)		
Intercept	0.002	0.35
Res_DON	**-0.380**	**-0.73**
r-squared	0.002	
Panel C: States with largest number of firms (n=576)		
Intercept	0.006	2.36
Res_DON	**0.300**	**1.00**
r-squared	0.006	

State-level regressions estimated using OLS.
States with smallest (largest) number of firms have a number of firms below (above) the median number of firms in a state each year.
Dependent variable is Mean_RCETR, state level mean of Res_CETR.
Res_DON is residual from regression of DONATE on population (in millions), estimated annually without year dummies.
Variables are defined in Appendix A.
t-statistics computed using standard errors clustered at the state level.

Table 9
Effect of different number of firms in a state on coefficient estimate

	(1)		(2)	
	States with smallest number of firms		States with largest number of firms	
Variable	Coef.	t-stat.	Coef.	t-stat.
Intercept	0.272	13.57	0.314	23.30
DONATE	**-0.301**	**-0.96**	**0.914**	**3.23**
SIZE	-0.000	-0.15	0.000	0.44
MB	-0.009	-2.19	-0.010	-6.05
LEV	-0.061	-3.34	-0.064	-14.36
CH	-0.025	-2.70	-0.027	-4.96
CHGNOL	0.159	2.46	0.166	11.03
ROA	-0.053	-1.59	-0.080	-4.86
EQUITY	-0.075	-0.13	-1.115	-4.31
PPE	-0.022	-1.39	-0.042	-4.14
INTANG	0.045	1.31	0.001	0.92
FI	0.362	2.78	0.210	1.98
STTAX	1.624	13.60	1.483	42.00
NOLDUM	-0.072	-7.57	-0.054	-17.67
year dummies	yes		yes	
ind. dummies	yes		yes	
r-squared	0.166		0.168	
n=	6,525		59,618	

Firm-level regressions estimated using OLS.
States with smallest (largest) number of firms have a number of firms below (above) the median number of firms in all states each year.
Dependent variable is Cash_ETR.
Variables are defined in Appendix A.
t-statistics computed using standard errors clustered at the state level.

Table 10

Effect of extremely high (H) or low (L) values of ETRs and donations on results

	Dependent variable is state-level mean of residual ETR: Mean_CETR	
Variable	Coefficient	t-statistic
Panel A: Remove H/H and L/L firm-level observations		
Intercept	0.005	2.02
Res_DON	**-0.374**	**-1.29**
r-squared	0.009	
Panel B: Remove H/H firm-level observations		
Intercept	0.004	1.63
Res_DON	**-0.159**	**-0.51**
r-squared	0.002	
Panel C: Remove L/L firm-level observations		
Intercept	0.007	2.74
Res_DON	**0.085**	**0.29**
r-squared	0.000	

State-level (n = 576) regressions estimated using OLS.
States with smallest (largest) number of firms have a number of firms below (above) the median number of firms in all states each year.
H/H observations have Res_CETR and Res_DON in highest 5% of observations for the year.
L/L observations have Res_CETR and Res_DON in lowest 5% of observations for the year
Dependent variable is Mean_RCETR, state level mean of Res_CETR.
Res_DON is residual from regression of DONATE on population (in millions).
Variables are defined in Appendix A.
t-statistics computed using standard errors clustered at the state level.