The Effect of Volunteering on Women's Wages: Evidence from the United States

By

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Abstract

This thesis estimates the wage return of volunteer work among women in the United States. Counter to previous comparable estimations for the US, my identification strategy can handle the highly endogenous motive of self-selection into volunteer work using information of precipitation. I identify local average treatment effects (LATE) using state-level variation of precipitation as an instrument, which creates exogeneous variation among individuals at different states in their volunteer labor supply. I find that precipitation's effect on volunteer activity is heterogenous across the United States, since it mostly affects compliers at those states which are classified with snow climates. Because of the huge regional wage differences in these states, I show that the use of nominal wages as a dependent variable violates the independence assumption of the LATE estimation and downward biases the estimation results, while the use of living-cost-adjusted wages can eliminate this bias. My results show no evidence of significant wage returns of volunteer activity among compliers; however, the characterization of compliers shows that they are weakly attached to the labor market.

JEL Classification: C26, D64, J31,

Keywords: volunteer wage return, local average treatment effect, precipitation

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Contents

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List of Figures

List of Tables

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1. Introduction

Even if time is money, nearly 63 million Americans did not remember Benjamin Franklin's phrase when they offered their manpower to charitable organizations for free during 2010; or, did they? Despite the fact that nearly one-quarter of adults in the United States take part in voluntary work, we do not know exactly how unpaid work affects volunteers' lives and their labor market opportunities. The common "do volunteer work" advice to unemployed workers suggests that it may have more advantage than just the pleasure of helping others; however, probably the larger part of American volunteers do charitable work to serve their community rather than to benefit themselves. Even if the volunteers do not take into consideration their future benefits from charitable work, it may affect indirectly their wages or employment, which – due to the large number of volunteers – could have a significant effect on the whole economy as well.

Based on the 2011 volume of the Panel Study of Income Dynamics (PSID), this indirect connection between volunteerism and wages seems to be straightforward, since volunteers earn nearly 9 thousand dollars more yearly than non-volunteers on average. However, charitable workers tend to have a more favorable socio-economic status than non-volunteers: according to the Bureau of Labor Statistics, they are more likely to be college graduates and married, while they are less likely to be a member of a minority group, differences which may partly explain the existing wage gap between volunteers and non-volunteers. Due to these discrepancies, it seems that the decision to volunteer or not is highly endogenous, which makes the measurement of volunteer work's effect on labor market outcomes difficult as researchers have not yet quantified reliable causal effect between voluntarism and wages in the USA. In this thesis I addresses this gap in the literature, namely I examine whether voluntary work has an effect on women's wages in the United States.

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I build on the work of Cozzi et al. (2017) who first used IV estimation to measure the wage returns of volunteer activity: they used rainfall as an instrument on British wages to overcome the afore-mentioned endogeneity problem. They argue that regional differences in rainfall creates exogeneous variation in the decision of volunteer labor supply, since the alternative cost of indoor voluntary work is smaller in regions where the outside leisure opportunities are limited due to the high average yearly rainfall. I adapt their argument to the United States, where I show using cross-section data from PSID that even the state-level differences in precipitation can explain variation of the women's participation in volunteer activity. Since the amount of precipitation is orthogonal to any kind of socio-economic attributions of the workers, using precipitation as an instrument I could estimate the volunteer work's unbiased local average treatment effect (LATE) on women's wages. Estimating the LATE, I find that volunteer activity does not affect women's living-cost-adjusted wages significantly, but it surprisingly reveals that the instrumented volunteer variable does not fail in the test of exogeneity.

My thesis contributes to the existing literature of volunteerism in three different ways. First, to the best of my knowledge, this work is the first which uses an IV method to estimate the wage return of volunteer work among women in the United States. Second, I show that if there is regional co-movement between wages and precipitation, the usage of nominal wages as a dependent variable violates the independence assumption of the LATE framework and leads to biased estimation; however, I find that the adjustment of nominal wages with price parity indices can abolish this source of bias. Finally, I show that precipitation is an appropriate instrument to predict volunteer activity only in US regions with a snow climate, and since the effect of precipitation on volunteer work is the strongest during the winter, it seems that precipitation affects volunteerism through transport difficulties caused by snow.

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The rest of the thesis is organized as follows. In the next chapter I discuss that the IV estimation of volunteer activity's economic return only recently emerged in the literature. In Chapter 3, I describe my identification strategy and the main assumptions behind it, show why my estimation results depends on the different climate zones at the United States, and report the main differences among volunteers' and non-volunteers' attributions in the sample. I report my estimation results and main findings in Chapter 4, in which I also characterize compliers and check the robustness of my result. Finally, I conclude my findings and suggest potential future improvements in Chapter 5.

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2. Literature review

The literature of the volunteerism's economic analysis has emerged as early as the middle of the 19. century, although the literature mostly focused on wartime volunteer activity until the end of 1960's. Mueller (1975) was one of the first who used regression analysis to explain why people, and especially women take part in volunteer activity; however, her results do not show clear evidence on which factors mostly affect women's decisions on their volunteer hours allocation. During the 1960's, beside the prestige and altruistic motives, Mueller (1975) identifies human capital accumulation as one of the main reasons for women to participate in volunteerism, because – due to the lack of enough part time job positions – at that time volunteer work was among the few opportunities for mothers with small children to maintain or increase their human capital.

While Mueller (1975) also mentions consumption and investment-related rewards of voluntary work, Menchik and Weisbrod (1987) were the first who isolated clearly these two effects. They estimate a Tobit model with similar controls to Mueller (1975) to measure if volunteer work and charitable giving are more likely to be complements or substitutes. They find a negative connection between wages and volunteered hours (their estimated net wage elasticity of volunteer work is –0.4), while they show that volunteer activity and donations to charity organizations seem to be more complements than substitutes. Bauer et al. (2013) confirms this substitution effect among those who cannot maintain their high-level volunteer labor supply, but they also show that charity donation and free work for nonprofit organizations strongly correlate with each other, especially for religious organizations.

Freeman (1997) also corroborates Menchik and Weisbrod's (1987) negative wage elasticity of volunteer work, but he also points out that even if wealthier and more capable workers tend to spend less time on volunteering, they are also more likely to participate in

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volunteer activities (Day and Devlin (1998), Bauer et al. (2013) and Cozzi et al. (2017) also verify this finding). Freeman (1997) argues that volunteer work is a "conscience good", which means that people who are asked to participate in charitable activity tend to do so, even under prohibitively high alternative costs. Thus, Freeman's paper suggests that consumption utility plays a non-negligible role in charity time allocation, which means that pure investment-oriented approach could be misleading during the examination of volunteer behavior. The findings of Neymotin (2016) strengthen the importance of consumption utility in volunteer work decision: she shows that people tend to do more volunteer work if their local communities do so, which phenomenon is hardly explainable with the pure investment motivation of volunteerism. Bruno and Fiorillo (2012) also verify Freeman's argument, showing that neither the consumption, nor the investment motive alone can explain the volunteer behavior in Italy, while Sauer (2015) reports that even if both motivation plays a crucial role in volunteer decision, almost three-quarter of the lifetime utility gain of charitable work comes from the human-capital investment side of volunteerism.

Unlike the previous authors who examine which characteristics and motivation affect the decision about the supply of voluntary work, Day and Devlin (1998) estimate how volunteer activity affects labor income through the increase of human capital. In an OLS framework, they show that volunteers earn 6.6 percent more on average after controlling for personal characteristics; however, they identify quite big differences among different types of volunteer activities. According to their results, voluntary work for religious organizations has the highest negative effect on wages, it decreases workers' salary by 18 percent, while sports-related and economics-oriented charity activities increases their payroll by 8 and 18 percent, respectively (although the later result is only marginally significant). These huge differences illustrate well the potential endogeneity problems with Day and Devlin's (1998) approach, which do not consider why people choose various types of organizations to volunteer for. It is hard to imagine

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that religious work would lower volunteers' salary so much; it is more likely that those involved to religious unpaid work who value more the charity than their salary. Thus, the lack of an exogenous source to involve in volunteer activity does not mitigate the potential self-selection bias toward volunteer work, which means that the usual OLS framework cannot identify properly the true effect of charitable work on wages.

To reduce the selection bias, Petrovski et al. (2017) use an instrumental variable approach to test if volunteer activity decreases the possibility of becoming unemployed: their results show that there is no significant connection between volunteerism and employability. They instrumented the volunteer activity with the childhood tradition of volunteerism in family and with the current volunteer activism of any family member of the respondent. However, as Petrovski et. al. (2017) mentions, their instruments may lack truly exogenous variations. As previous studies and my next chapter also shows, parents with more favorable socio-economic backgrounds tend to volunteer more, and as their children are more likely to maintain their parent's favorable income and educational level, the author's instruments may also affect directly respondents' wages. To enhance the exogeneity of their instruments, Petrovski et al. (2017) control for parents' socio-economic background with their education and income level, but compared to Cozzi et al. (2017), their identification strategy is less clear and convincing.

Counter to the previous authors, Cozzi et al. (2017) elegantly solves the potential endogenous problems during the measurement of volunteer activity's wage return: using rainfall as an instrument for become a volunteer, they find that volunteer activity has significant and economically large positive effect on wages in the United Kingdom (4,859 pounds for men and 3,096 pounds for women, respectively). To verify their IV approach, they argue that the difference in rainfall across regions creates exogenous variation in the alternative cost of volunteer activity, since bad weather decreases the attractiveness of outdoor and increases the attractiveness of indoor activities, such as voluntary work (which is mostly taken place inside

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in the UK). Because of the construction of their identification strategy, Cozzi et al. (2017) shows that the estimated wage differentials should be interpreted as local average treatments effects (LATE), which in the case of women means that those women who do volunteer work just because live in a rainy environment earn 3,096 pounds more than those who do not volunteer, because the more favorable weather condition broadens their leisure opportunities. Besides the high first stage F-test, Cozzi et al. (2017) do not present any formal test for the endogeneity of the rainfall instrument in their framework, while – as my results show later – even an appropriate instrument could fail the test of endogeneity if there are positive relationship between earnings and rainfall differences among regions.

Mainly because of the lack of quasi-experiments with exogenous variation of involving in volunteer activity, the selection-bias-free literature which estimates volunteer work's effect on wages is narrow. As they state, Cozzi et al. (2017) present the first paper which measure this effect with an IV approach; however, it is not clear whether rainfall is a generalizable instrument outside the United Kingdom. As I see, it is a gap in the literature, which my work can fill.

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3. Data and Identification Strategy

3.1. Data Sources

Like most of the aforementioned work, mine is also built on a panel survey, because usually tax data and other official registers do not contain information about individuals' volunteer habits. Like Sauer (2015), I use the Family and Individual-level data collection of Panel Study of Income Dynamics (PSID), which beyond the necessary information of volunteer activity contains well-detailed employment and earnings data. Besides many advantages of this database, the PSID stopped collecting volunteer information regularly in 2005 and since then the main data collection only asked about volunteer activity in 2011. Because of the lack of information about volunteerism directly before and after 2011, I could use only one year's data, so my results are based on cross-section data instead of a more information rich panel one. Thus, because of that data limitation I cannot control for long standing working and volunteer habits of individuals; however – as Cozzi et al. (2017) shows – my identification strategy is more appropriate for cross-section or pooled data sources than panel data.

Another limitation of the PSID database is that its publicly available dataset does not contain information about the proper resident city, or at least resident county location of each interviewee, which limits the exogeneous variation of my instrument. During the estimation I use precipitation data as instruments to find exogeneous variation in the decision on volunteer activity, because – as Cozzi et. al. (2017) also did – I assume that weather can incite or dissuade at least some of the interviewees to do volunteer activity. Thus, to get reliable first and second stage estimations, I should have had as accurate information about the weather of interviewees' residency as possible, but because of the lack of county information at publicly available PSID database I could only use the state-level averages of weather characteristics. This deficiency may weaken the accuracy of my estimation; however, if we accept the assumption that the

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weather is roughly homogeneous in each state (which except the western states of the United states seems to be a reliable assumption, based on the work of Kotten et al. (2006)), the estimation which is based on state-level variation of weather characteristics should lead to fairly similar results to those estimation which based on county-level data.

Thus, because of the data limitation I use state-level precipitation data as instruments during the estimation: I downloaded this information – which can be found in Table A12 and A13 in the Appendix – from *currentresults.com* website, which collected them form the National Climatic Data Center of the National Oceanic and Atmospheric Administration. The precipitation data are state-level yearly averages between 1971 and 2000, while the used snow data are yearly averages between 1981 and 2010 from more important cities at each state. These cities are mainly state capitals (such as Minneapolis, Indianapolis or Boston), but some of them are cities with larger population than the state capital (Birmingham at Alabama, or Portland at Oregon) or cities with more central location (Lansing at Michigan or Harrisburg at Pennsylvania). During the analysis I assume that the city-level snow data are generalizable for the whole state, which is also based on the homogeneous state-level weather assumption. During the analysis I used Kottek et al. (2006) and the *climate-data.org* website to identify the main climate of the Köppen-Geiger climate classification system for each state, which I will introduce at the next section.

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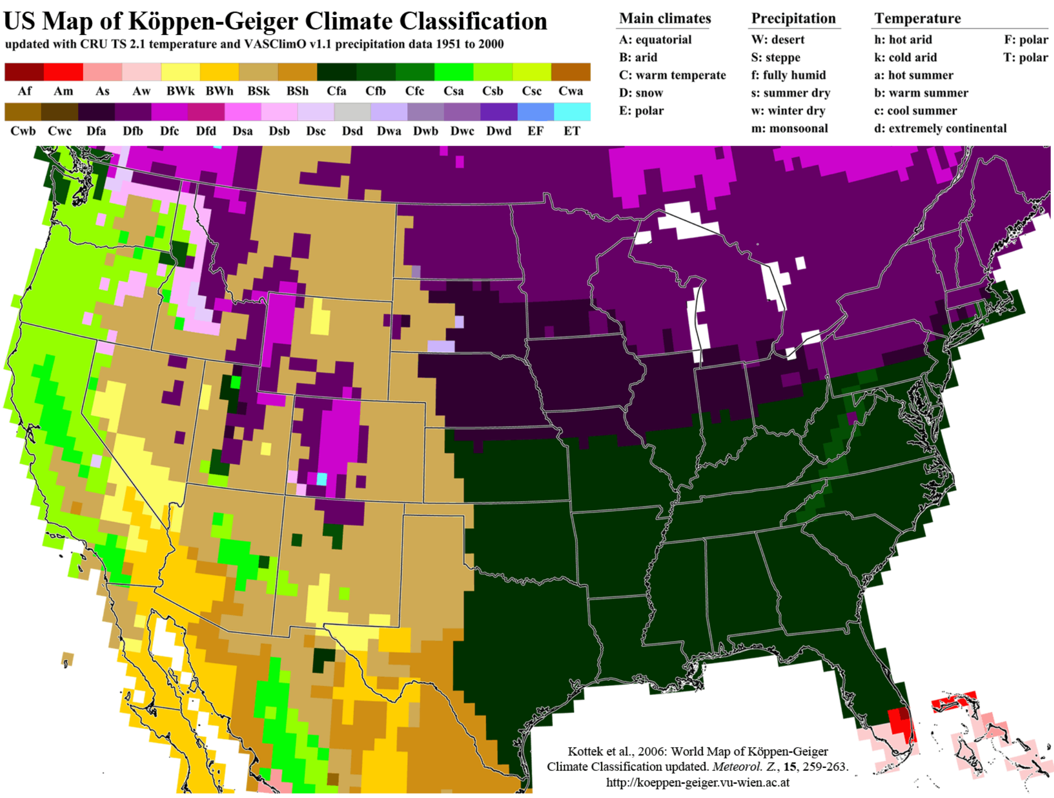
3.2. Köppen-Geiger climate classification system

To adopt the rainfall-based instrument idea of Cozzi et al. (2017) to the United States, first I need to control for climatic differences across the United States. As work by Kottek et al. (2006) or Chen and Chen (2013) shows – despite remarkable differences in precipitation across regions – the climate is warm temperate in the United Kingdom, which means that the coldest month’s average temperature is greater than –3 °C in the whole country and there are no serious seasonal fluctuations in precipitation, which is mainly rain. Because of the similar weather conditions across the United Kingdom, Cozzi et al. (2017) could assume that the amount of precipitation has the same effect on the volunteer decision of interviewees, independently of their exact residency. As the Köppen-Geiger climate classification will show, this assumption would be misleading for the United States, since the country’s climate is far from identical. Because of the heterogeneity in weather conditions, I cannot assume that the amount of precipitation has the same effect on each individual, since snow can limit more volunteer activity than rainfall. Mainly because of the different type of winter precipitation, any analysis which uses precipitation as an instrument and does not take into account the climate differences shall lead to biased estimation.

FIGURE 1: KÖPPEN-GEIGER CLIMATE CLASSIFICATION MAP OF THE UNITED STATES



Source: Kottek et al. (2006)

To distinguish different climate zones in the United States I use the Köppen-Geiger climate classification system, which is one of the most well-known of these classifications

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among climatologists. As Chen and Chen (2013) summarize, the system compresses monthly average precipitation and temperature data into an easily characterizable three-digit code, from which the first digit indicates the main climate of the given territory. As Figure 1 shows, there are four out of five types of main climate in the conterminous United States; however, equatorial climate only occurs in South Florida. Using Kottek et al.'s (2006) description for the main climatic zones, almost all of the southern, as well as the pacific states can be characterized by warm temperate climates (indicated with green in Figure 1), while most states at the North Central and Northeast regions have snow climate (indicated with purple). The main difference between these two major climate zones is that the coldest month average temperature is greater than –3 °C in warm temperate climate states, which means that the monthly winter precipitation in snow climate states is mainly snow. As my results will show, this difference makes significant variation in decision about volunteer work. The non-pacific states of the West region are mainly characterizable with snow or arid climate (indicated with brown and yellow in Figure 1) and because of the Rockey Mountain, these states' climate seems to be more heterogeneous than others. Unlike warm temperate and snow climate, arid climate has no formula in the classification system for average monthly temperature; arid climate is only characterized by little precipitation, which is often exposed to serious seasonal fluctuation.

Since the second digit of the Köppen-Geiger codes are based on the precipitation of the given area – which I use as an instrument – I only used the first-digit of the climate classification system during estimation. Many states (such as Colorado, Texas or Indiana) are not homogeneous in climate zones, so I had to assign a main climate zone to each state. Based on the *climate-data.org* website, I appoint each state to that climate zone which characterize the most inhabited areas at the given state. Table A15 at the Appendix represents the final climate classification of states.

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3.3. Descriptive statistics

To avoid unnecessary bias in the estimated causal effect of volunteering, I had to slightly narrow my original dataset. Since the volunteer-related questions only target the head of a family and his/her spouse, my sample does not contain other family members for whom the database would contain information otherwise. Because of my research question, first I restricted my sample to women, then I narrowed it for those individuals who are between 20 and 70 years old. I also dropped those whose primary activity was not work for salary in the job market; thus, there are no students or retired citizens in the sample, even if they worked for a salary at 2010. With these restrictions I can reduce the possible endogeneity of the working decision, because – as Sauer (2015) argues – I do not have to explain formally why these individuals decided to retire or continue their education. Since my main interest is the volunteer work's causal effect on wages, I also rule out those individuals who did not work during 2010, or whose yearly average hourly salary was lower than 7.25 dollars/hour, which was the federal minimum wage at that time.

As Table 1 shows, 1,424 women remain in the sample after exclusions, from which 345 took part in volunteer activity in 2010. Since the 2011 volume of the PSID survey does not contain information about frequency or yearly hours of volunteer activity, I identify every woman as a volunteer who did any kind of volunteer work for an organization during 2010 at least once (in their work, Day and Devlin (1998) and Cozzi et al. (2017) also use the same definition for volunteers). In the sample almost every fourth women participated in volunteer activity in 2010, which is less than the 29.3 percent of the national average what the Bureau of Labor Statistics (2011) reported for 2010. If we compare the subgroup of volunteers and non-volunteers, in many aspects they seem to be nearly identical. There is only small difference between the two groups in number of children, age, working habits or urbanization, while non-

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volunteers only marginally have more work experience and tenure at their current workplace than volunteers.

TABLE 1: DESCRIPTIVE STATISTICS

	Whole sample	Among	
		volunteers	non-volunteers
Volunteer dummy	0.24 (0.43)	1	0
Salary (dollars)	36,567 (29,407)	44,165 (31,050)	34,140 (28,453)
Living-cost-adjusted salary (dollars)	37,086 (28,731)	44,910 (29,733)	34,587 (27,959)
Age (years)	39.77 (12.07)	38.73 (11.74)	40.10 (12.16)
Work experience (years)	12.05 (9.10)	11.63 (8.48)	12.19 (9.28)
Tenure at current workplace (years)	6.79 (7.82)	6.39 (7.17)	6.92 (8.02)
Average weekly hours at 2010	39.90 (10.62)	40.49 (10.89)	39.71 (10.52)
Worked 52 weeks at 2010	0.82 (0.38)	0.84 (0.37)	0.82 (0.39)
Work in management	0.10 (0.30)	0.15 (0.26)	0.09 (0.28)
Racial distribution			
Black	0.46 (0.50)	0.36 (0.48)	0.49 (0.50)
White	0.46 (0.50)	0.57 (0.50)	0.42 (0.50)
Hispanic	0.08 (0.27)	0.07 (0.26)	0.08 (0.27)
Asian	0.01 (0.09)	0.01 (0.08)	0.01 (0.09)
Other	0.01 (0.09)	0.00 (0.08)	0.01 (0.10)
Highest education			
Primary education	0.01 (0.08)	0	0.01 (0.09)
Started high school	0.07 (0.26)	0.02 (0.15)	0.09 (0.28)
Completed high school	0.24 (0.43)	0.13 (0.34)	0.28 (0.45)
1 year of college education	0.11 (0.31)	0.09 (0.28)	0.11 (0.32)
2 year of college education	0.20 (0.40)	0.18 (0.38)	0.21 (0.40)
3 year of college education	0.06 (0.23)	0.07 (0.26)	0.05 (0.22)
4 year of college education	0.17 (0.38)	0.25 (0.43)	0.15 (0.31)
At least started graduate studies	0.14 (0.35)	0.26 (0.44)	0.10 (0.31)
Married	0.12 (0.32)	0.18 (0.38)	0.10 (0.30)
Number of children	0.83 (1.13)	0.76 (1.03)	0.85 (1.16)
Less than 2 years old	0.09 (0.28)	0.08 (0.27)	0.09 (0.29)
More than 2, but less than 6 years old	0.13 (0.34)	0.12 (0.33)	0.14 (0.34)
Live in metropolitan area	0.76 (0.43)	0.77 (0.42)	0.76 (0.43)
Number of observations	1,424	345	1,079

Note: Standard errors in parenthesis

However, based on the sample it seems that there are systematic differences in education, marriage, occupation status and salaries between volunteers and non-volunteers, which

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coincide with the findings of the existing literature (such as Day and Devlin (1998), Bauer et al. (2013) or Cozzi et al. (2017)). With the overrepresentation of whites and underrepresentation of blacks among volunteers compare to the whole sample, it may seem that whites are more likely to participate in volunteer activity than blacks. According to the sample, married women are also more likely to volunteer, while managers are also overrepresented among volunteers. More than half of the volunteers in the sample studied in a four-year college or started graduate studies, while this is true only for one-fourth of non-volunteers, who are twice as likely to stop their education after high school graduation than volunteers.

Because – at least partly – of these differences, volunteers earned nearly 30 percent more than non-volunteers. Based on the more than 10 thousand dollars wage difference among the two subgroups, a naïve conclusion would suggest that volunteer activities have a huge positive effect on wages. My results will show that this is not exactly the case. However, the above-mentioned differences illustrate well the endogeneity problem of measuring voluntary activity's economic effect on workers: without further analysis we do not know if volunteers tend to earn more because volunteer activity increased their human capital, or they do volunteer activity because they earn enough money to consume "conscience goods" too.

3.4. Identification strategy

To overcome the above-mentioned endogeneity problem, one should find an instrument with exogeneous variation which affects workers' decision about their voluntary labor supply, while it is also independent from those main characteristics which affect directly their wages (such as education, occupation or working habits). Cozzi et al. (2017) suggest rainfall as an adequate instrument: they argue that as the rainfall narrows the scope of possible outdoor activities, it also lower the alternative cost of the indoor voluntary work. If we accept the

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reasonable assumption that any characteristics of workers which affect their wages are independent from the weather (which means that more capable workers do not concentrate on places just because of the more favorable weather), the amount of rain or other type of precipitation creates the required exogenous variation in the following model:

$$V_i = \alpha_0 + \pi P_s + \gamma X_i + u_i \tag{1}$$

$$S_i = \alpha_1 + \omega \hat{V}_{i,s} + \gamma X_i + \varepsilon_i \tag{2}$$

where I use the variation of rainfall as an instrument in a two-stage least square (2SLS) estimation. As equation (1) show, at the first stage I use state-level precipitation (P_s) and set of individual-level characteristics (X_i) to predict the probability of being volunteer (V_i) for each individual, then at the second stage I used the predicted volunteer variable from the first stage to estimate ω, which – under the subsequent four assumptions – can be interpreted as the local average treatment effect (LATE) of volunteer work on wages (S_i). The LATE estimation takes into account that the amount of precipitation does not have an equal effect on everyone: some citizens do volunteer work independently of the weather conditions, some of them do not participate in volunteer activities. As Angrist et al. (1996) argues, the LATE shows the voluntary work's effect on compliers' wages who do charity work in nice weather conditions, but do not in unfavorable ones. Following Angrist et al. (2000), four conditions should hold to identify the estimated effect as LATE:

1. Independence assumption

The independence assumption requires true exogeneity of the instrument, which means that precipitation should be as good as randomly assigned. In other words, there should not be strong connection between precipitation or any other characteristics of individuals, which seems to be a plausible assumption. Thus, using the LATE estimation as an identification strategy, I indirectly assume that weather conditions do not have a serious

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effect on people's lifetime decisions, such as years of education or number of children, but this does not mean that weather conditions could not affect their decisions about going or not to a charity event. As Table A14 in the Appendix shows, the amount of precipitation does not correlate strongly with the set of controls, which strengthens the plausibility of that independence assumption in this application.

2. Exclusion assumption

This restriction requires that the precipitation should not affect worker's wages directly, only through the volunteer activity. The assumption that salaries are independent from precipitation also seems to be reasonable for most of workers.

3. First stage

The third assumption requires that precipitation has a significant effect on volunteer work decision, an assumption which is testable. In the next chapter I will show that more precipitation significantly reduces the likelihood of doing volunteer work for those who live in states with snow climate. The direction of the precipitation's effect on volunteerism is opposite than in the United Kingdom, which may mean that volunteers are more likely do outdoor charity works than indoor ones in the US, or the weather conditions affect transportation more in the US (which could be the case in heavy snow).

4. Monotonicity

In our case, this restriction means that if precipitation affects someone's decision on volunteer activity, it should affect it in the same way for everyone. Thus, using LATE I assume that there is no one who would volunteer for an organization in a rainy state who would not in a drier one, which also seems to be a feasible assumption.

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As Angrist et al. (1996) shows, under these four assumptions the estimated IV coefficient can be interpreted as a local average treatment effect. During the estimation I use both continuous and dummy variables of precipitation as an instrument, which requires a different interpretation. Using a continuous variable, the estimated parameter shows how much more those women earn who do volunteer activity under a small amount of precipitation, but not under a huge amount of it. Since the "small" and "huge" amount of precipitation is not a clear cut-off, the interpretation of LATE with dummy instrument is much clearer. Since the defined dummy variable's value is 1 if the worker lives in a state where the annual (or seasonal) precipitation is greater than the national average, the estimated coefficient shows how much more salary those women get who do charity work if they live in a state with less precipitation than the national average, and would not do voluntary work if they lived in a state with more precipitation than the national average.

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4. Results

During the estimation I used the same set of controls for every 2SLS specification, which – excluding the white dummy – contains all variables under the dashed line at Table 1, plus I added the square of experience and various industry and occupation dummies to them. The industry and occupation dummies are based on the 3-digit industry and occupation classification of the 2000 Census, which was reported in the PSID database. I also used the PSID's classification for regional dummies, which is identical to the U.S. Census Bureau-designated regions (Table A15 at the Appendix shows this classification too). Because of the large set of controls and the modest number of observations from states with arid climate (only 39 individuals), I estimate model specifications at three different samples. First, I examine whether the precipitation instrument can explain the variation in volunteer activity in the whole country, then I narrow my analysis to states with snow or temperate climate.

I characterize precipitation variables as good instruments if they meet the test of weakness. To test this criterion, I use the first-stage F-test, which examines if the precipitation can explain the variation of participation in volunteer activity; in the next pages when I use the phrase "F-test", I always refer to the F-test of the following hypothesis at the first-stage: $\pi=0$. To avoid the potentially large bias of weak instrument, the value of the F-test should be greater than at least 10, which means that precipitation certainly affects the decision about volunteer activity. Thus, when I use one instrument, F-test and t-test at the first stage test the same hypothesis, which means that if an instrument meets the F-test, it should also have significant π coefficient at the first stage. But even if an instrument meets the F-test, the use of 2SLS over an OLS specification also requires the true endogeneity of the instrument; thus, I use the Wu-Hausman test to examine the endogeneity of the volunteer activity. Under an endogenous instrumented variable, the 2SLS specification is preferred over OLS, because the former is consistent but the latter is not. But if the Wu-Hausman test shows that we cannot reject the null

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about the exogeneity of the instrumented variable, the OLS estimation is more efficient and therefore also preferred over the 2SLS one.

4.1. Results based on nominal salaries

Table 2 presents twelve separate regression results which were estimated on the whole sample. These specifications only differ in the first stage instruments (P_s in equation (1)), which are shown in the first column of the table. The second column of Table 2 presents the estimated π parameters in equation (1), which shows the precipitation's effect on volunteering: if this coefficient is significantly different from zero, it means that the amount of precipitation truly affects volunteer decision. The results in the second column show little evidence of the feasibility of precipitation as an instrument for volunteerism in the full sample, as precipitation significantly affects volunteer activity only under the winter precipitation dummy (which value is 1 if the interviewee lives in a state where the winter precipitation is larger than the national average, and 0 otherwise). Thus, the estimated coefficient of the winter precipitation dummy shows that the likelihood of participation in volunteer activity significantly decreases by 7.8 percent among women who live in states with more winter precipitation than the average.

The fifth column of Table 2 shows the estimated wage returns of volunteer activity among compliers, which are represented by ω in equation (2). Since most of the first-stage instruments do not have significant effect on volunteer activity, all estimated wage returns are unreliable except the one which is estimated with the winter precipitation dummy. Using this variable as an instrument, the estimated ω coefficient becomes –40,317, which would mean that the wage return of volunteer work among compliers is nearly –40,000 dollars.

However, since the value of the winter precipitation dummy's first-stage F-test at the sixth column is slightly smaller than 10, the estimation result at the fifth column also do not

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seem to be reliable, because it does not meet the test of weak instrument. The small F-stats of other specifications also confirm that precipitation only has negligible effect on volunteering.

TABLE 2: RESULTS ON THE WHOLE SAMPLE, BASED ON NOMINAL SALARIES

	1. stage		2. stage		Postestimation	
Instrument	π	R^2	ω	R^2	First-stage F-stat.	Wu-Hausman (p-value)
Precipitation (100 mm)						
Annual (cont.)	–0.005 (0.004)	0.12	45,382 (50,250)	0.11	1.75	0.25
Spring (cont.)	–0.014 (0.015)	0.12	110,459 (131,007)	0.00	0.85	0.06
Summer (cont.)	–0.001 (0.010)	0.12	526,639 (4,709,459)	0.00	0.01	0.21
Fall (cont.)	–0.026 (0.018)	0.12	33,366 (43,072)	0.28	2.08	0.39
Winter (cont.)	–0.028 (0.013)	0.12	–1,323 (24,833)	0.46	4.86	0.92
Annual (dummy)	–0.034 (0.027)	0.12	169 (40,709)	0.47	1.63	0.98
Spring (dummy)	–0.040 (0.027)	0.12	11,540 (36,763)	0.35	2.16	0.78
Summer (dummy)	–0.032 (0.027)	0.12	–30,338 (46,229)	0.28	1.37	0.42
Fall (dummy)	–0.007 (0.026)	0.12	80,927 (364,895)	0.00	0.07	0.71
Winter (dummy)	–0.078*** (0.025)	0.13	–40,317** (20,339)	0.14	9.85	0.01
Snow (cm)						
Annual (cont.)	–0.000 (0.000)	0.12	–85,748 (89,177)	0.00	1.69	0.10
Annual (dummy)	–0.007 (0.030)	0.12	–184,071 (793,331)	0.00	0.06	0.45

Notes: All 2SLS specifications differ only in the instruments, the sample size is 1,424. The set of controls contains the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. Robust standard errors are in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Thus, because of the mostly insignificant first-stage results and the small value of F-tests, the results in Table 2 show little evidence of the feasibility of precipitation as an instrument for volunteer work across the whole US. However, since the winter precipitation's F-test is much larger than any other seasons' test value among both continuous and dummy instruments, precipitation may play a more important role in the decision of volunteer work in winter than in other seasons. The explanation of the importance of winter rainfall may be that different

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types of precipitation have different effects on the decision about volunteer work, namely snow prevents more people from doing volunteer work than rain. To test this explanation, first I narrow my sample to states with temperate climate, where the winter precipitation is mostly rain. Based on the small insignificant first-stage results and the small F-stats in Table 3, precipitation is a weak instrument in regions with temperate climate, which suggests that precipitation has no effect on volunteer activity in states with temperate climate.

TABLE 3: RESULTS ON STATES WITH TEMPERATE CLIMATE, BASED ON NOMINAL SALARIES

	1. stage		2. stage		Postestimation	
Instrument	π	R^2	ω	R^2	First-stage F-stat.	Wu-Hausman (p-value)
Precipitation (100 mm)						
Annual (cont.)	0.003 (0.005)	0.19	–212,926 (406,467)	0.00	0.27	0.01
Spring (cont.)	0.004 (0.018)	0.19	–596,829 (2,413,550)	0.00	0.06	0.00
Summer (cont.)	0.008 (0.011)	0.19	–127,959 (197,820)	0.00	0.47	0.05
Fall (cont.)	0.014 (0.023)	0.19	–198,583 (325,955)	0.00	0.36	0.01
Winter (cont.)	–0.000 (0.019)	0.19	2,590,984 (298,000,000)	0.00	0.00	0.54
Annual (dummy)	0.043 (0.035)	0.19	–31,065 (40,909)	0.31	1.56	0.33
Spring (dummy)	–	–	–	–	–	–
Summer (dummy)	0.029 (0.035)	0.19	–84,273 (57,238)	0.00	2.63	0.00
Fall (dummy)	–	–	–	–	–	–
Winter (dummy)	–	–	–	–	–	–
Snow (cm)						
Annual (cont.)	–0.000 (0.001)	0.19	–737,735 (4,254,176)	0.00	0.03	0.00

Notes: All 2SLS specifications differ only in the instruments, the sample size is 801. The set of controls contains the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. Specifications with spring, fall and winter dummies cannot be estimated because of collinearity. Robust standard errors are in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

However, as Table 4 shows, winter precipitation has a greater effect on volunteer activity in states with snow climate than in the whole United States: the value of F-tests of the

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continuous winter precipitation instrument rises from 4.86 to 10.21, while the value of the winter precipitation dummy goes up from 9.85 to 14.34. In parallel with the rising F-statistics, both winter precipitation instruments' first stage coefficient becomes significant with a non-negligible magnitude: according to the continuous variable, 100 mm more precipitation in the winter decreases the likelihood of the participation in volunteer activity by 9.7 percent.

TABLE 4: RESULTS ON STATES WITH SNOW CLIMATE, BASED ON NOMINAL SALARIES

	1. stage		2. stage		Postestimation	
Instrument	π	R^2	ω	R^2	First-stage F-stat.	Wu-Hausman (p-value)
Precipitation (100 mm)						
Annual (cont.)	–0.030*** (0.010)	0.15	–23,022 (20,101)	0.34	10.45	0.31
Spring (cont.)	–0.073** (0.035)	0.14	–15,861 (32,027)	0.38	4.33	0.65
Summer (cont.)	–0.110*** (0.039)	0.14	–37,688** (17,513)	0.21	8.09	0.01
Fall (cont.)	–0.124*** (0.035)	0.15	–26,491 (19,594)	0.32	12.22	0.23
Winter (cont.)	–0.097*** (0.031)	0.15	–15,069 (24,229)	0.39	10.21	0.58
Annual (dummy)	–0.127*** (0.046)	0.14	–19,892 (21,961)	0.36	7.51	0.41
Spring (dummy)	–0.128*** (0.048)	0.14	–20,365 (23,101)	0.36	7.18	0.42
Summer (dummy)	–0.159*** (0.054)	0.15	–38,553** (17,486)	0.20	8.70	0.00
Fall (dummy)	–0.064 (0.044)	0.13	–31,877 (50,326)	0.27	2.13	0.53
Winter (dummy)	–0.149*** (0.040)	0.15	–40,815** (19,944)	0.18	14.34	0.03
Snow (cm)						
Annual (cont.)	–0.0007*** (0.0002)	0.14	–45,416* (27,030)	0.12	11.39	0.03
Annual (dummy)	–0.067* (0.04)	0.14	–36,243 (35,036)	0.23	3.00	0.20

Notes: All 2SLS specifications differ only in the instruments, the sample size is 584. The set of controls contains the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. Robust standard errors are in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Based on these results, it seems that potential volunteers who live in a snow climate area are more sensitive to precipitation than others: almost all first-stage coefficients become

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significantly different form zero, while their negative signs show that – counter to the British example of Cozzi et al. (2017) – precipitation has a negative effect on volunteer activity in the USA. According to the endogeneity tests – which requires close to zero p-values at the last column – and the tests of weak instrument, two of the twelve 2SLS specifications seem to estimate the volunteer wage return of women correctly: both the winter precipitation dummy's and the continuous snow variable's F-test are greater than the threshold value of 10, while based on the Wu-Hausman tests we can reject the exogeneity assumption of the volunteer activity in these specifications. According to these estimations, volunteer work has a huge negative and significant effect on compliers' wage: the estimated wage return of volunteer work among compliers is between –40,000 and –45,000 dollars, which is incredibly high compared to the nearly $36,500 average wage in the sample.

This huge negative effect is not only unprecedented in the literature which mostly finds a small positive effect, but also questions why women take part in activities which cause a huge pay loss for them. The consumption utility of volunteer activity may explain a small negative effect, but this magnitude seems to be a deterrent for workers. The estimated effect also contradicts the investment motive of volunteer work, because a huge negative wage effect would mean that human capital degrades during charitable activity. Thus, this result creates a puzzle, namely why women participate in voluntary work if it has such a huge negative effect on their wages and human capital. I think the solution to this puzzle is based on regional wage differences, which shows why a regional-based instrumental variable approach should first eliminate the regional differences at the dependent variable.

As Table 5 suggests, this huge negative effect is mostly coming from the wage and volunteer activity differences among the Northeast and North Central regions, which are the two dominating regions in the snow-climate zone. In both regions volunteers earn more than non-volunteers; however, volunteers' average wage is smaller in the North Central region than

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non-volunteers' average salary at the Northeast. The huge wage difference may be the effect of the different economic or industrial structure of the two regions, but the predicted wage differences contradict this presumption: using the usual set of controls and regional dummies, an OLS estimation shows that workers earn significantly less in the North Central region than in the Northeastern area.

TABLE 5: REGIONAL DIFFERENCES IN WAGES, PRECIPITATION AND VOLUNTEER ACTIVITY

	Northeast	North Central	South	West
Salary (dollars)				
Among volunteers	60,506	39,130	40,340	47,929
Among non-volunteers	42,824	32,114	30,858	37,992
Predicted wage difference to Northeast region (dollars, based on wage regression)	0	–6,304** (2,715)	–6,382*** (2,175)	–1,922 (2,396)
Cost of living index	105	92	94	99
Living-cost-adjusted salary (dollars)				
Among volunteers	57,625	42,533	42,915	48,413
Among non-volunteers	40,785	34,907	32,828	38,376
Predicted wage difference to Northeast region (living-cost-adjusted dollars, based on wage regression)	0	–286 (2,561)	–1,211 (1,969)	–467 (2,241)
Precipitation (mm)				
Annual	1,146	802	1,241	464
Spring	290	225	329	118
Summer	303	277	332	92
Fall	296	193	287	113
Winter	256	108	293	142
Snow (yearly, cm)	138	89	25	60
Ratio of volunteers	0.196	0.327	0.215	0.258
Number of obs.	199	349	703	229

Notes: During the calculation of wage differences with an OLS specification, I regress wages on the controls I used in previous specifications and on newly added reginal dummies. Robust standard errors are in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

This wage difference biases downward the estimated volunteer work's effect on wages, since employees earn less and do more volunteer work in the North Central region: the huge estimated negative effect of the 2SLS model would suggest that compliers earn less because they do volunteer work, while – based on the regional differences – it is more likely that

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compliers earn less because they are more likely to live in the lower-wage North Central region. Thus, the significant wage difference between regions violates the independence assumption of LATE estimation, because it seems that precipitation has a positive co-movement with wages in the snow climate area. However, the South region illustrates well that this positive co-movement does not mean causal relationship, because even if the amount of precipitation is higher in the South region, the wages are lower than in the Northeast.

4.2. Results based on living-cost-adjusted salaries, single instrument

To overcome the positive co-movement between regional wages and precipitation in the snow climate zone, I created living-cost-adjusted salaries with the state-level regional price parity index of the St. Louis Fed. Table 5 illustrates that not only wages but also price level are higher in the Northeast than at the North Central region, thus living-cost-adjusted salaries represent better the purchasing power of wages in each state than nominal wages. As the predicted living-cost-adjusted wage differences shows in Table 5, the regional wage differences disappear if we measure them with living-cost-adjusted wages: none of the regional dummies' coefficient is significantly different from zero, thus the usage of living-cost-adjusted wages does not violate the independence assumption of the LATE estimation.

Since only the dependent variable changes in these specifications compared to the estimations at the previous section, only the estimations' second-stage can change. This means that the F-stat of each specification remains unchanged. Thus – as Table 6 shows – the potential set of appropriate specifications contains five elements which meet the weak instrument test, and all of them are estimated on the sample of states with snow climate. However, each of these specifications with an F-test larger than 10 fails to meet the endogeneity test of an instrument:

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the high p-values of the Wu-Hausman test shows that we cannot reject the exogeneity of volunteer activity, which means that OLS specifications are preferred over 2SLS ones.

TABLE 6: 2SLS POSTESTIMATION RESULTS, BASED ON LIVING-COST-ADJUSTED SALARIES

	Whole sample		Snow Climate		Temperate climate	
Instrument	1. stage F-stat.	Wu-Hausman (p-value)	1. stage F-stat.	Wu-Hausman (p-value)	1. stage F-stat.	Wu-Hausman (p-value)
Precipitation (100 mm)						
Annual (cont.)	1.75	0.98	10.45	0.71	0.27	0.76
Spring (cont.)	0.84	0.58	4.33	0.83	0.06	0.68
Summer (cont.)	0.01	0.48	8.09	0.02	0.47	0.71
Fall (cont.)	2.08	0.86	12.22	0.80	0.36	0.92
Winter (cont.)	4.86	0.94	10.21	0.85	0.27	0.76
Annual (dummy)	1.63	0.77	7.51	0.81	1.56	0.39
Spring (dummy)	2.16	0.84	7.18	0.75	–	–
Summer (dummy)	1.37	0.08	8.70	0.00	0.71	0.53
Fall (dummy)	0.07	0.60	2.13	0.66	–	–
Winter (dummy)	9.85	0.51	14.34	0.67	–	–
Snow (cm)						
Annual (cont.)	1.69	0.97	11.39	0.62	0.03	0.40
Annual (dummy)	0.06	0.99	3.00	0.84	–	–
Sample size	1,424		584		801	

Notes: All 2SLS specifications in rows differ only in the instruments. The set of controls contains the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. Specifications with spring, fall and winter dummies in the temperate climate region cannot be estimated because of collinearity (all instruments are zero in the sample).

As Table 7 shows, the OLS point estimates under various samples are positive and their magnitude seem to be reasonable; however, the effect of volunteer work on women's living-cost-adjusted wages is not significantly different from zero at all three different samples. Thus, my results with single instrument show that volunteer work does not affect complier women's wages. Based on these results, volunteer work does not increase compliers' human capital as much as it becomes visible in wages; while, it may have a positive effect on employment, the measurement of this effect is out of the scope of this thesis.

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TABLE 7: OLS REGRESSION RESULTS

	Whole Sample	Snow climate	Temperate climate
Volunteer dummy's coefficient	1,999 (1,740)	1,117 (3,323)	2,680 (1,824)
R^2	0.47	0.42	0.60
Number of observations	1,424	584	801

Notes: During the calculation I regress living-cost-adjusted wages on the volunteer dummy and controls, which contain the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. Robust standard errors are in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Even if the insignificance of the results is not shocking, the failed exogeneity tests contradict the literature and the apparently huge differences in descriptive statistics among volunteers and non-volunteers. According to Table 1, it seems that volunteers significantly differ from non-volunteers in education, race and managerial occupancy, but the Wu-Hausman test suggests that these differences do not significantly affect compliers' wages. As the robustness checks will show, the puzzle of the exogeneity of the volunteer activity does not depend on the choice of the sample: even if we add or subtract female workers to the sample according to their relations to the labor market, the Wu-Hausman test does not show evidence of endogeneity. One way to tackle this puzzle, I think one should estimate the model with more punctual information about women's residence, which would create more variation in the precipitation instrument. The reason behind volunteer work's exogeneity may be – particularly among western states – the inappropriate assumption about state-level climate homogeneity, which – because of the lack of data – I should have assumed during the estimation.

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4.3. Results based on living-cost-adjusted salaries, multiple instrument and interaction terms

Another way to tackle the above-mentioned exogeneity puzzle may be the use of more than one instrument during the estimation, which measure whether joint seasonal differences among states could explain the differences in volunteer activity. To test this possibility, I used various combination of continuous and dummy variables during the estimation on states with snow climate, which results are represented in Table 8 and 9. Because of the use of more than one instrument, the first stage of the estimation changes to the following equation:

$$V_i = \alpha_0 + \pi_1 P_s^1 + \ldots + \pi_i P_s^i + \gamma X_i + u_i \tag{3}$$

where i is the number of used instruments during the estimation, while P_s^i is the precipitation variable in different season in state s.

Like in the previous sections, an appropriate combination of instruments should have higher F-stat than 10 to meet the test of weak instrument, while Wu-Hausman test's small p-value should also show the endogeneity of the volunteer variable at the second stage of the estimation. However, counter to the previous sections, the F-tests in Table 8 measure the joint significance test of instruments (namely whether $\pi_1 = \ldots = \pi_i = 0$, where i may be any number between 1 and 4), thus a smaller than 10 value of the F-test indicates that the given combination of instruments is weak. For example, as Table 8 shows, using both the continuous fall and winter precipitation variable as an instrument in the first stage, it reveals that even if separately neither instrument is weak, jointly they are, because the F-stat of the combination of these two instruments is only 6.22. An appropriate combination of instruments should also meet the test of overidentifying restrictions as a third criterium, which tests whether at least one of the instrument correlates with the error term of equation (2): a small p-value of this test would suggest that there is no correlation between the two, which is a necessary condition for consistency.

Since the number of the possible combination of the four dummies and four continuous seasonal precipitation variables is quite large, first I test the combination of dummy and continuous variables separately. Table 8 contains the postestimation results of all possible combination of seasonal variables for both continuous (between the second and fourth column)

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and dummy variables (between the fifth and seventh column). The first column of the table shows the used combination of instruments during the estimation: for example, the "(2), (3)" combination means that I used the summer and fall precipitation variable as instruments at the first stage. Just for comparison, I add the postestimation results of single instruments which take place at the first four rows of Table 8; these results are identical to the results in Table 6.

TABLE 8: 2SLS POSTESTIMATION RESULTS, USING CONTINUOUS AND DUMMY VARIABLES SEPARATELY

	Using only continuous variables			Using only dummy variables		
Instrument(s)	1. stage F-stat.	Wu-Hausman (p-value)	Overid. (p-value)	1. stage F-stat.	Wu-Hausman (p-value)	Overid. (p-value)
Spring (1)	4.33	0.83	–	7.18	0.75	–
Summer (2)	8.09	0.02	–	8.70	0.00	–
Fall (3)	12.22	0.80	–	2.13	0.66	–
Winter (4)	10.21	0.85	–	14.34	0.67	–
(1), (2)	4.07	0.01	0.40	4.41	0.01	0.33
(1), (3)	6.83	0.79	0.89	3.87	0.84	0.33
(1), (4)	5.46	0.72	0.31	7.70	0.68	0.97
(2), (3)	6.26	0.65	0.14	5.33	0.02	0.31
(2), (4)	6.21	0.71	0.13	8.56	0.12	0.22
(3), (4)	6.22	0.94	0.21	7.23	0.57	0.41
(1), (2), (3)	5.20	0.19	0.22	3.58	0.02	0.58
(1), (2), (4)	7.25	0.17	0.15	5.78	0.06	0.47
(1), (3), (4)	4.92	0.93	0.24	5.20	0.56	0.63
(2), (3), (4)	4.32	0.77	0.32	5.70	0.10	0.47
(1), (2), (3), (4)	5.45	0.18	0.29	4.34	0.06	0.68

Notes: All 2SLS specifications in rows differ only in the instruments which are shown in the first row. I used living-cost-adjusted wages as dependent variable in all specifications. The set of controls contains the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. The sample size is 584.

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As Table 8 shows, none of the combination of the four seasonal precipitation variables meets the required three criteria, since all combination's F-value is smaller than 10. Moreover, all combination's F-stat are smaller than the highest F-stat of the used instruments, and all overidentification tests show potential correlation between at least one of the instruments and the error term. The results suggest that using more than one variable does not help to find appropriate combination of instruments to estimate the wage return, it only raises the possibility of the violation of the conditional mean assumption.

Even if the use of purely continuous or purely dummy set of instruments do not lead to find the appropriate postestimation result, the combination of them may lead to find the proper combination of instruments. To test this possibility, I combined one dummy and one continuous variable with high F-test as a single instrument and use them as pair of instruments during the estimation; the last three columns of Table 9 present the postestimation statistics of these estimations. The first column of the table presents the estimated combination, where the (C) and (D) represent whether the used instrument is a continuous or dummy variable, respectively. As the results present, the combination of dummy and continuous variables as instruments does not lead to find appropriate set of instruments, since all specifications fail in all three required tests.

TABLE 9: 2SLS POSTESTIMATION RESULTS, USING INTERACTION TERMS OF CONTINUOUS AND DUMMY VARIABLES

	Using the interaction term of the two variables as an instrument		Using both variables as separate instruments		
Instruments	1. stage F-stat.	Wu-Hausman (p-value)	1. stage F-stat.	Wu-Hausman (p-value)	Overid. (p-value)
Spring (D), Summer (C)	7.02	0.72	4.63	0.27	0.27
Spring (D), Fall (C)	8.97	0.74	6.25	0.78	0.79
Spring (D), Winter (C)	9.45	0.78	5.27	0.96	0.14
Summer (D), Fall (C)	10.97	0.07	6.97	0.19	0.24
Summer (D), Winter (C)	10.51	0.53	6.43	0.36	0.19
Winter (D), Summer (C)	13.83	0.65	8.74	0.26	0.17
Winter (D), Fall (C)	14.37	0.65	8.24	0.72	0.86

Notes: In each row, (C) and (D) represent whether the used instrument is a continuous or dummy variable, respectively. All 2SLS specifications in rows differ only in the instruments, which are shown in the first row. I used living-cost-adjusted wages as dependent variable in all specifications. The set of controls contains the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. The sample size is 584.

However, as the second and third columns in Table 9 show, the use of interaction terms of dummy and continuous variables lead to better postestimation results. I constructed these interaction terms with the multiplication of the dummy and continuous variables in the first

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row, which makes the interpretation of the interaction terms more difficult. For example, the use of the interaction term of the spring precipitation dummy and the continuous summer precipitation variable as an instrument measures how the summer precipitation affects the volunteer activity of women in states where the spring precipitation is higher than the national average. As Table 9 shows, the F-test of interaction terms (which test whether $\pi = 0$ at equation (1)) are higher than the F-tests of using both variables as separate instruments (which test whether $\pi_1 = \pi_2 = 0$ at equation (3)), which suggests that interaction terms are more likely leading to appropriate estimation. Despite the relatively high F-tests' of interaction terms, the higher than 5 percent p-values of the Wu-Hausman tests show potential exogeneity of the volunteer activity, which queries the use of 2SLS estimation method. Thus, it reveals that neither the use of multiple instruments, nor the use of interaction terms solve the above-mentioned exogeneity puzzle without the exact knowledge of residence of interviewees.

4.4. Characterization of compliers

As Angrist and Pischke (2006) argue, LATE estimation is not only useful to identify the treatment effect on compliers, but to compute their ratio in the whole sample and characterize their main attributes. As the previous sections show, precipitation's effect on volunteer work is the highest during the winter, thus to get more punctual characterization of compliers, I use the winter precipitation dummy during the estimation in this section.

In our case, the ratio of compliers can simply be computed as the following:

$$P(compliers) = |E[V_i|\, WP = 1] - E[V_i|\, WP = 0]|$$

where V is the voluntary and WP is the winter precipitation dummy (which value is one if the winter precipitation is higher at the given state that the national average), while the reason behind the necessity of the absolute value is the negative correlation between volunteer work

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and winter precipitation. After computation it reveals that nearly 10 and 13 percent of the women are compliers at the whole sample and at the set of states with snow climate, respectively, which is relatively high compared to 29.3 percent, which was the ratio of volunteers among women at 2010, according to Bureau of Labor Statistics (2011).

The characterization of compliers is based on a similar 2SLS estimation as equation (1) and (2) represent. The first stage of the estimation does not change, but the second stage transforms to the following equation:

$$D_i X_i^j = \alpha_1 + \omega \hat{V}_{i,s} + \gamma X_i + \varepsilon_i \tag{4}$$

where X_i represents the set of controls and X_i^j is an element of this set (such as years of experience, or married dummy). According to Angrist and Pischke (2006), in this specification ω shows the average of X_i^j attribution among compliers, which are presented in Table 10.

Most of the estimated characteristics seem to be reasonable in Table 10. Only the connection between experience and tenure is odd, since the former cannot be higher than the latter. However, even if the estimated value of these two variables contradict each other, comparing them to sample averages reveals that compliers tend to have less work experience than the sample average and their tenure at their present employment is more likely longer, while they worked less week at 2010 in average than non-compliers. In both sample compliers are more likely whites, whose education levels do not differ significantly from the sample mean. They do not tend to have more children than non-compliers, but they are more likely married and older then the sample average.

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TABLE 10: AVERAGE CHARACTERISTICS OF COMPLIERS

	Whole sample		Snow climate	
	All individual	Compliers	All individual	Compliers
Work experience (years)	12.05 (9.10)	8.62*** (2.96)	11.78 (9.03)	8.42*** (2.33)
Tenure at current workplace (years)	6.79 (7.82)	9.81*** (2.69)	6.83 (7.94)	11.59*** (2.46)
Average weekly hours at 2010	39.90 (10.62)	38.57*** (3.48)	39.81 (11.19)	41.58*** (3.09)
Worked 52 weeks at 2010	0.82 (0.38)	0.75*** (0.12)	0.83 (0.37)	0.77*** (0.10)
Work in management	0.10 (0.30)	–0.05 (0.12)	0.10 (0.30)	0.12 (0.08)
Racial distribution				
Black	0.46 (0.50)	0.35** (0.15)	0.32 (0.47)	0.19 (0.12)
White	0.46 (0.50)	0.60*** (0.16)	0.63 (0.48)	0.72*** (0.13)
Hispanic	0.08 (0.27)	0.07 (0.08)	0.06 (0.23)	0.10* (0.06)
Asian	0.01 (0.09)	–0.00 (0.01)	0.01 (0.07)	–
Other	0.01 (0.09)	0.03 (0.03)	0.00 (0.06)	–
Years of education	13.92 (2.16)	14.04*** (0.59)	14.15 (2.10)	14.34*** (0.46)
Married	0.12 (0.32)	0.34*** (0.13)	0.15 (0.35)	0.33*** (0.10)
Number of children	0.83 (1.13)	0.90*** (0.33)	0.75 (1.05)	0.36 (0.27)
Less than 2 years old	0.09 (0.28)	0.16* (0.09)	0.09 (0.29)	0.13** (0.07)
More than 2, but less than 6 years old	0.13 (0.34)	0.11 (0.10)	0.11 (0.31)	–0.00 (0.08)
Age	39.77 (12.07)	42.63*** (4.33)	39.69 (12.50)	42.68*** (3.56)
Live in metropolitan area	0.76 (0.43)	0.58*** (0.15)	0.76 (0.42)	0.83*** (0.10)
Number of observations	1,424	1,424	584	584

Notes: Column two and four contains sample averages with their standard error. All 2SLS specifications at column three and five differ only in the dependent variable, which was the multiplication of the volunteer dummy and the given variable at the first column in each row. The set of controls contains the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. Robust standard errors are in parenthesis at the third and fifth column. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Beyond the previous characteristics, there are some in which compliers differ in the two sample. Based on the whole sample, compliers are more likely to live in rural areas, while their

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weekly worked hours are slightly smaller than the sample mean; by contrast, compliers living in states with snow climate tend to work more hours a week and they are more likely to live in metropolitan areas. All in all, based on the previous characteristics, compliers tend to be weakly attached to labor market: despite compliers' higher age, they have less experience and work less weeks during the year, while the insignificant managerial dummy also shows that complier women are not likely to work at higher positions.

4.5. Robustness check of the results

To check the robustness of my findings, I estimated the model with various definition of the sample in the snow climate area with the winter precipitation dummy. During the previous estimations I drop those women from the sample who were not between 20 and 70 years old at 2010, whose primary activity was not work at the job market, who did not work during 2010 and whose hourly wage was lower than 7.25 dollar, which was the federal minimum wage at that time. I call this definition of the sample the baseline scenario in Table 11. With this definition of the sample I could exclude women who were only marginally attached to the labor market (as students or pensioners who only worked some weeks during 2010) and whose hourly wage reflects data reporting mistakes, because these observations could bias downward the estimated effect of volunteer work on wages. Table 11 present the estimation results under different definition of the sample: the first five specification diminishes or tightens one restriction compared to the baseline scenario, while scenarios in the seventh and eighth rows use a combination of these additions.

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TABLE 11: ROBUSTNESS CHECKS

Instrument	Num. of obs.	1. stage Coeff.	1. stage R2	2. stage Coeff.	2. stage R2	Postestimation F-test	Postestimation Wu-Hausman (p-value)
Baseline	584	–0.149*** (0.040)	0.15	–6,582 (15,864)	0.41	14.34	0.67
Only age between 25 and 65 (1)	523	–0.147*** (0.042)	0.15	–7,175 (18,438)	0.40	12.20	0.70
Adding students and pensioners (2)	616	–0.147*** (0.038)	0.15	–10,863 (15,643)	0.41	15.01	0.51
Worked 52 weeks in 2010 (3)	487	–0.136*** (0.045)	0.15	–3,000 (20,228)	0.39	9.44	0.84
Hourly wage can be lower than 7.25 $/h (4)	706	–0.113*** (0.036)	0.15	7,296 (19,226)	0.43	9.91	0.79
Worked more than 1,000 hours at 2010 (5)	521	–0.141*** (0.043)	0.15	–6,010 (18,761)	0.40	10.79	0.76
Only those who strongly attached to labor market (1)+(3)+(5)	429	–0.141*** (0.048)	0.17	–326 (22,761)	0.39	8.76	0.94
Adding those who weakly attached to labor market (2)+(4)	769	–0.110*** (0.040)	0.14	738 (18,098)	0.44	10.80	0.98
No restriction	1,289	–0.073*** (0.025)	0.14	–28,782 (26,752)	0.28	8.27	0.24

Notes: All 2SLS specifications differ only in the different definition of the snow climate sample, the instrument was the winter precipitation dummy for all estimation. The baseline scenario contains all women between 20 and 70 years old whose revealed primary activity is work at the labor market, and who worked at least 1 week at 2010 for at least 7.25 $ hourly wage, which was the federal minimum at 2010. The set of controls contains the variables under the dashed line at Table 1, plus industry and occupational dummies, and the square of experience. Robust standard errors are in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

As Table 11 shows, abolition of all baseline rules increases the sample size from 584 to 1,289, while first-stage coefficient of the "no restriction" scenario also shows that winter precipitation has a significantly negative effect on volunteer activity; however, the dropping F-value of the first-stage shows that the instrument does not explain enough variation in volunteer activity. Since all first-stage coefficients are negative and significantly different from zero, the winter precipitation affects volunteer activity independently from the definition of the sample, and as the F-test is mostly larger, or only slightly smaller than its threshold value of 10, the winter precipitation dummy seems to be a valid instrument under most of the specifications. Examining the F-tests' change, it seems that the broader definition of the sample – which contains those whose primary activity is not work, such as students and pensioners – tends to

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increase, while narrowing the sample only for those who strongly attached to the labor market tends to decrease the value of the F-test.

As the Wu-Hausman test shows no evidence of endogeneity of the instrument under neither specification, it seems that a different definition of the sample would not help to tackle the exogeneity puzzle of my results. In total, robustness checks at least show that the relevance of the winter precipitation dummy is robust to various definition of the sample, while the relevance of an instrument increases with the addition of women who were weakly attached to the labor market.

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5. Conclusion

In this thesis I estimated the wage return of volunteer work among women in the United States. Counter to previous comparable estimations for the US, using precipitation data as an instrument I could handle the highly endogenous motive of self-selection into volunteer work. As Cozzi et al. (2017) present, the various amount of precipitation creates exogeneous variation in the alternative cost of volunteer work, which enabled to draw a causal effect between volunteer work and wages. I showed that precipitation has a significant effect on compliers' volunteer activity mainly in those states which – based on the Köppen-Geiger climate classification system – are classified with snow climates.

Using this exogeneous variation I identified the local average treatment effect (LATE) of the volunteer work on salaries, which differs substantially under various measurement of the wages. Because of the huge regional wage differences among states, the usage of nominal wages as a dependent variable violates the independence assumption of the LATE estimation and downward biases the estimation results, while I showed that the usage of living-cost-adjusted wages can eliminate this bias. Using living-cost-adjusted wages, I did not find evidence of the significant wage return of the volunteer work. The characterization of compliers showed that compliers usually work less than a random worker, while they are also more likely older but have less experience; based on these results, it seems that compliers tend to be weakly attached to the labor market.

Despite the fact that my results seem to be robust to different definitions of the sample, the addition of more detailed location information may change my results, while it would certainly improve the precision of the first stage estimation. Without the knowledge of the proper resident city or county of workers, I should have assumed that weather is heterogeneous within states, which probably does not hold for many western states. The addition of more

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detailed location information would also increase the variation in precipitation, which may reveal a significant effect of the precipitation on volunteer activity also in states with a temperate warm climate. As another addition, distinguishing between the effect of different types of charity organization would also increase the precision of the estimated wage returns, because – as Menchik and Weisbrod (1987) suggest – volunteer work may not have a homogeneous effect on human capital accumulation.

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Appendix

TABLE A12: AVERAGE PRECIPITATION IN US STATES BETWEEN 1971-2000 (MM)

	Ann.	Spr.	Sum.	Fall	Win.		Ann.	Spr.	Sum.	Fall	Win.
Alabama	1480	408	351	309	408	Nebraska	599	198	237	123	42
Arizona	345	60	105	87	93	Nevada	241	72	45	57	66
Arkansas	1284	381	273	330	303	New Hampshire	1103	270	300	294	240
California	563	147	21	111	288	New Jersey	1196	315	324	288	270
Colorado	405	120	138	90	60	New Mexico	370	63	156	102	51
Connecticut	1279	330	321	330	294	New York	1062	261	297	288	219
Delaware	1160	306	309	276	270	North Carolina	1279	315	366	300	300
Florida	1385	276	543	324	243	North Dakota	452	114	204	99	36
Georgia	1287	318	360	264	348	Ohio	993	270	303	225	195
Idaho	481	132	84	114	153	Oklahoma	927	294	246	252	132
Illinois	996	288	300	240	168	Oregon	695	177	66	174	279
Indiana	1060	300	312	249	198	Pennsylvania	1089	279	315	273	222
Iowa	864	249	333	204	81	Rhode Island	1218	321	273	309	315
Kansas	733	228	270	168	66	South Carolina	1264	291	384	282	309
Kentucky	1242	351	318	270	303	South Dakota	511	165	207	105	36
Louisiana	1528	399	375	348	405	Tennessee	1376	393	321	303	360
Maine	1072	267	282	282	240	Texas	734	192	207	207	129
Maryland	1131	300	303	273	258	Utah	310	87	66	84	72
Massachusetts	1211	309	297	312	291	Vermont	1085	258	321	288	216
Michigan	833	201	252	234	147	Virginia	1125	297	303	273	252
Minnesota	693	168	297	171	57	Washington	976	222	99	264	399
Mississippi	1499	441	327	315	417	West Virginia	1147	309	333	252	255
Missouri	1071	315	300	282	174	Wisconsin	829	207	315	216	90
Montana	390	114	138	81	57	Wyoming	328	108	99	75	45

Source: *currentresults.com*

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TABLE A13: AVERAGE PRECIPITATION IN US STATES BETWEEN 1981-2100 (CM)

State	City	Snow	State	City	Snow
Alabama	Birmingham	4.1	Nebraska	Lincoln	65.8
Arizona	Tucson	0.8	Nevada	Reno	55.4
Arkansas	Fort Smith	13.2	New Hampshire	Concord	154.4
California	San Diego	0	New Jersey	Atlantic City	41.9
Colorado	Grand Junction	48.5	New Mexico	Albuquerque	24.4
Connecticut	Hartford	102.9	New York	Syracuse	314.5
Delaware	Wilmington	51.3	North Carolina	Greensboro	19.3
Florida	Tampa	0	North Dakota	Bismarck	130
Georgia	Macon	1.8	Ohio	Columbus	69.9
Idaho	Boise	48.8	Oklahoma	Oklahoma City	19.8
Illinois	Peoria	62.5	Oregon	Portland	7.6
Indiana	Indianapolis	65.8	Pennsylvania	Harrisburg	71.6
Iowa	Des Moines	88.6	Rhode Island	Providence	85.9
Kansas	Wichita	37.3	South Carolina	Columbia	1.3
Kentucky	Louisville	31.8	South Dakota	Huron	111.5
Louisiana	New Orleans	0	Tennessee	Nashville	16
Maine	Portland	157	Texas	Dallas	3.8
Maryland	Baltimore	51.3	Utah	Salt Lake City	142.7
Massachusetts	Boston	111.3	Vermont	Burlington	206.2
Michigan	Lansing	129.8	Virginia	Richmond	26.2
Minnesota	Minneapolis	137.2	Washington	Seattle	12.7
Mississippi	Jackson	2.3	West Virginia	Beckley	157.5
Missouri	Springfield	43.2	Wisconsin	Madison	129.3
Montana	Helena	96.8	Wyoming	Lander	232.2

Source: *currentresults.com*

TABLE A14: CORRELATION BETWEEN PRECIPITATION AND THE SET OF CONTROL VARIABLES

Control	Corr.	Control	Corr.
Age	0.0199	Highest education (dummies)	
Work experience (years)	0.0575	Primary education	–0.1029
Tenure at current workplace (years)	0.0599	Started high school	–0.0230
Average weekly hours at 2010	0.0078	Completed high school	0.0593
Worked 52 weeks at 2010 (dummy)	–0.0030	1 year of college education	0.0188
Work in management (dummy)	–0.0922	2 year of college education	0.0652
Racial distribution (dummies)		3 year of college education	–0.0084
Black	0.3257	4 year of college education	–0.0566
White	–0.2044	At least started graduate studies	–0.0598
Hispanic	–0.1774	Married (dummy)	–0.0586
Asian	–0.0844	Number of children	0.0484
Other	–0.0343	Less than 2 years old	0.0404
Live in metropolitan area (dummy)	–0.0717	More than 2, but less than 6 years old	0.0308

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TABLE A15: REGION AND CLIMATE CLASSIFICATION OF STATES

Region / climate zone	Snow Climate	Temperate Climate	Arid Climate
Northeast	Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont		
North Central	Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin		
South	Kentucky, West Virginia	Alabama, Arkansas, Delaware, Florida, Georgia, Louisiana, Maryland, Mississippi North Carolina, Oklahoma, South Carolina Tennessee, Texas, Virginia	
West	Utah, Colorado, Idaho,	California, Oregon, Washington	Arizona, Montana, Nevada, New Mexico, Wyoming

Notes: the composition of regions is identical to the U.S. Census Bureau Regions. I sort states into main Köppen-Geiger climate classes based on *climate-data.org* website: I appoint each state to that climate zone which characterize the most inhabited areas at the given state.

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