Impact of Social Transfers on Depressive Symptoms: Evidence from the South African Old Age Pension

Adeola Oyenubi and Joseph Ajefu

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Adeola Oyenubi*and Joseph Ajefu†

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Abstract

We study the effect of income receipt in form of Old age pension (OAP) on the prevalence of depressive symptoms using the Centre of Epidemiologic Studies Short Depression Scale (CES-D 10). We exploit the exogeneous age eligibility criteria in a regression discontinuity (RD) design to estimate the impact of OAP on depressive symptoms. Using the randomized inference approach, we find a statistically significant evidence that the OAP reduces depressive symptoms among the beneficiaries. We find this effect vary by gender and employment status. Our result also suggests that the impact of OAP tends to increase with depression scores, that is, those with high depression score tend to benefit more. We note that since the CES-D 10 is a screening tool, this result only provides an indication that the expected positive relationship between income and health holds in this context.

JEL classification: I14, I15. I18

Key words: Mental health, causal inference, old age pension, South Africa

1 Introduction

The effect of social transfers in form of Old Age Pension (OAP) on health outcomes is gaining traction in development discourse in recent years. An emerging research has reported a positive relationship between OAP income and well-being (Kaushal, 2014; Golberstein 2015; Grogan and Summerfield, 2019; Kollamparambil and Etinzock, 2019). However, the effect of OAP income on mental health in general and depressive symptoms and perceived stress (in particular) has largely been overlooked. By conjecture, since poverty has been found to be

**School of Economics and Business Sciences, University of the Witwatersrand; adeola.oyenubi@wits.ac.za

†Newcastle Business School, Northumbria University, Newcastle Upon Tyne, United Kingdom, United Kingdom; joeajefu@gmail.com

an important risk factor for mental health disorders, the receipt of pension income can play a significant role in reducing mental health disorders as measured by depressive symptoms (Lund et al, 2010)[1].

Golberstein (2015) argues that there are two reasons why one should expect income to affect mental health. First, the conventional Grossman health production model implies that health status improves with income by pushing out the budget constraint (Grossman, 1972). Second, in the case of mental health, psychosocial stress is a major risk factor. Therefore, the hypothesis is that since factors like income and financial well-being can be argued to be sources of psychosocial stress, they can also impact on the mental well-being of individuals.

In this paper, we examine whether an exogeneous income transfers to the elderly affect the prevalence of depressive symptoms in this population. We provide an answer to this question by examining the causal effect of the South African Old Age Pension on depressive symptoms. The South African Old Age Pension is a monthly cash transfer to older adults and the eligibility is determined by age and a means test. Both men and women have equal age eligibility of 60 years or older. In addition to the age eligibility, household income is used to determine the means test for either singles or married individuals (Amber, 2016).

The main challenge in addressing this question is to find an exogenous variation in income that eliminates potential reverse causation from health to income (Case, 2004). Also, another challenge is the problem of selection that can confound the causal effect of income on health. Hence, to identify the causal effect, we use a regression discontinuity (RD) design, which entails comparing the depression scores of those that meet the pension age-eligibility of 60+ years and the means test with those that meet these conditions but are below the cut-off.The conventional RD approach relies on non-parametric identification based on smoothness assumption. However, the RD approach we adopted was introduced by Cattaneo et al (2015) and relies on the idea of local randomization, that is, there is a window near the threshold where variation in treatment approximates a random experiment (Lee, 2008). Cattaneo et al (2016) introduce stata commands that can be used to implement this approach.

In our analysis, a possible change in the distribution of covariates around the cut-off age is a concern. Specifically, one may expect the distribution of gender on either side of 60 years to be different across gender groups. This is because based on the WHO figures, life expectancy is different for males and females in South Africa. The 2018 figures show that life expectancy for the males is 60.46 while it is 67.40 for the females[2]. Furthermore, employment status may evolve discontinuously at age 60 since many people retire around this age. These factors are important because depression has been shown to vary by these factors (Case and Menendez, 2009; Bubonya et. al, 2017). Indeed,

[1] Poverty can lead to mental health disorders through channels such as stress, social exclusion, decreased social capital, malnutrition, and trauma.

[2] See "https://countryeconomy.com/demography/life-expectancy/south-africa". Perhaps this reflects the fact that suicide rates are higher for men in South Africa (Kootbodien et. al, 2020)

as shown in our analysis below, it is difficult to find a window around the cut-off where gender and employment status are balanced. To deal with this, we disaggregate our analysis by gender and employment status.

Using the local randomization approach, we estimate the effect of OAP on depressive symptoms as measured by the 10-item Center for Epidemiological Studies–Depression (CES-D10). We find evidence that the OAP reduces depression scores in general and across the different subgroups (i.e. gender and employment status) considered. However, while this effect is statistically significant for some subgroups, it is not significant for some other groups (in some cases this can be attributed to sample size). Specifically, the effect is negative, but, not significant for the full sample and for those who are employed, for the unemployed, the effect is negative and significant[3].

Furthermore, the effect is negative for the two gender groups, but the effect is only significant (at 10%) for the males[4]. Disaggregating by gender for the employed, the effect remains negative for both males and females, but it is only significant for the females. For the unemployed, the result remains negative and significant for both gender groups (note that in this case, the negative and significant effect was only found for the unmarried females[5]). In terms of the size of the estimate, the effects can be arranged in the following way: (-1.78) female employed, (-1.61) male unemployed, (-1.10) female unemployed and finally (-0.68) male employed. This shows that the effect is heterogeneous across gender and employment status. While existing literature suggests that depression is more prevalent among women (Byers et al, 2010; Golberstein, 2015), our result suggests that this effect on gender groups is mediated by the distribution of employment status.

We also consider the possibility that the effect of OAP on depression may depend on the level of depression. The idea here is that those with higher level of depression may benefit more from the exogeneous income than others if the relationship between depression and income is non-linear for example. To examine this possibility, we model depression score as a count variable and estimate the quantile effect of receiving OAP. The result shows that at the higher (conditional) quantiles, the marginal effects are larger, negative and significant while at the lower quantiles, it is negative, but, not statistically significant.

Juxtaposing this with our disaggregated results will suggest that the employed women, unemployed men and unemployed women are benefiting more because they are starting from a lower base in terms of their level of depression

[3]We use National Income Dynamic Study (NIDS) wave 5 and the estimation sample includes only those who reported as being unemployed in that wave. The results remain the same when we consider the history of unemployment by restricting the sample to those who reported as being unemployed in waves 4 & 5. See details about our sample in the data in section 2.

[4]This result suggests that the effect is larger for males than for females which agrees with the result of Bubonga et. al (2017)

[5]For the full sample of the married and unmarried employed females, we did not find a window where the distribution of characteristics is balanced. The main issue is marital status. When we estimate for those who are not married alone (about 75% of that sample the effect is negative and significant).

before 60. In section 2, we provide evidence that shows that although in the population of people who qualify for the OAP, the depression score reduces when they hit age 60, this difference is larger and significant for the unemployed males and employed females even without controlling for covariates. It does appear that being employed tends to protect the males from depression while it does the opposite for the females. Perhaps this reflects the additional burden of home keeping that women have to grapple with relative to their male counterparts.

In general, our estimate shows that CES-D10 score is about 1 point lower for the beneficiaries of the OAP on the average. It should be noted that while the OAP is not endogenous to health because of the study design, there is a possibility that the individuals that are close to the eligibility threshold might become less depressed in anticipation of the benefit. Therefore, we interpret our estimate as a lower bound of the true effect estimate.

This paper is closely related to studies such as Belloni etal (2016), Golberstein (2015), and Chen et al. (2019). For instance, Golberstein (2015) examines whether social security retirement benefit "Notch" has an effect on mental health of older adults. The study finds that increases in social security income significantly improve mental health, but, mainly for women.

1.1 South African Old Age Pension

The South African Old Age Pension is a monthly cash transfer for older adults. In 2017, the OAP provides monthly income of R1, 600 for individuals over 60 years and R1, 620 for those over 75years. In the context of the poor in South African this amount is "large", it is larger than the upper poverty line in 2017 which stands at R 1 138/person/month (Statistics South Africa, 2019) and it is larger than other social pay-outs like the Child Support grant. This Social Assistance Eligibility is based on age and means test. In terms of age, the beneficiaries should be 60 years or older making age 60 the threshold (or cut-off) in the RD design, while in terms of the means test, the beneficiaries must not earn more than R78, 120 if they are single or R156 240 (combined income) if they are married. Furthermore, their worth in terms of assets should be at most R1.1 million if single or R2.3 million if married[6]. Amber (2016) notes that means test for eligibility is not binding for the vast majority of black South Africans, therefore, their paper and other studies on pension consider only age eligibility rule. This is plausible because Amber's sample is restricted to Africans. In our sample that cuts across race groups, we find that the distribution of employment status varies considerable for those below and above 60 years old[7]. In this study, we use both the means test and the age criteria to select the estimation sample[8].

[6] "https://www.gov.za/services/social-benefits-retirement-and-old-age/old-age-pension"

[7] Specifically, in the results not presented here in our final sample, only 9% of those over 60 are employed while about 48% of those under 60 are employed (note that in our sample, it is restricted to individuals between 50 and 80 years old). Under the randomized framework, we find that this variable remains significant irrespective of the window length. This is the case even when we restrict the sample to Africans only.

[8] OAP is administered by the South African Social Security Agency (SASSA). Qualifying individual has to apply to SASSA to receive the grant. Currently, the value of the grant

In terms of identifying the sample, we reckon with treatment on individual level, that is, treatment group members are those who reported benefiting from the OAP. We note that one could argue that individuals that share the same household with beneficiaries are partially benefiting from the grant under the assumption that households share resources. While this is plausible, the effect of OAP on depression score will be weaker for people who are not direct beneficiaries. One way to explain this is through the study by Ambler (2016) who finds that OAP increases women autonomy. The author explains that increase in bargaining power through increase in household income share is one channel through which OAP increases women autonomy. The idea here is that even though households may share resources, in terms of allocation of resources, the person who controls that resource do matter (Amber, 2016).

Therefore, if financial resource is a key source of psychosocial stress, the effect of income on the primary beneficiary will be larger than the indirect effect on other household members. To make sure that indirect beneficiaries do not form part of our comparison group, we drop all the indirect beneficiaries from our estimation sample. In other words, if someone is benefiting from OAP, but lives with someone who is not, the non-beneficiary is dropped from the sample irrespective of whether they qualify for the grant or not. To be clear, what this means is that individuals that share a household in our sample are either all receiving the grants or none of them is receiving the grant.

2 Data and Methodology

Our data source is the 2017 (Wave 5) South African National Income Dynamics Study (NIDS), we also use wave 4 of the data for robustness check. It is a longitudinal survey of individuals and households living in South Africa. We measure depressive symptoms with the 10-item Center for Epidemiological Studies–Depression (CES-D10) scale found in the National Income Dynamics Study (NIDS) Adult questionnaire.

The questions use a 4-point scale and ask if certain feelings or behaviour occur rarely or none of the time (assigned 1), some or little of the time (assigned 2), occasionally or a moderate amount of the time (assigned 3) or all the time (assigned 4). Responses are scored and the CES-D10 scale is the sum of these scores (see table A1 in the appendix for details). A higher CES-D score represents poorer mental health. Scores of 10 and above indicate depression (Radloff, 1997). This measure has been shown to be a valid and reliable screening toll in the context of South Africa (Baron et al, 2017).

As noted earlier, individuals are allocated to the treatment group based on the reported age and means test (which is based on the reported income and individual net worth in the survey). As noted by Amber (2016), because

is a maximum of R1,700 for people under 75years and R1800 for those over 75years. An applicant has to provide a number of documents to show that they qualify in terms of age and the means test which includes: South African identity card, proof of marital status, proof of income and/or dividends, proof of assets and proof of private pension if any.

eligibility cut-off is public knowledge, individuals may manipulate their age to benefit from the grant. This will invalidate the assumption that people just above and below the cut-off point are similar. However, this is unlikely for two reasons. First, unlike most African countries, South Africa has a robust identity documentation system that makes it easy to verify the age of grant applicants. The South African identity card is a required documentation to apply for the grant. Second, even if some respondents manipulate their age to benefit from the grant, there is no reason for these people to misreport their age in the NIDS survey. If there is manipulation, such individuals will not make it into our estimation sample because they will be dropped as their reported age in the survey will be less than 60 years [9].

As mentioned earlier, another concern is the possibility of the anticipated benefit affecting the outcome for otherwise qualified individuals below 60 years old. To account for this, we interpret our result as the lower bound of the true effect. Other concerns that deal with selection are explicitly dealt with under the local randomization approach. This is because the approach estimates the Local Average Treatment Effect (LATE), that is, our estimates are valid only in the window around the threshold where the distribution of (included) covariates are balanced across treatment arms. For example, the household size might vary with the anticipated pension receipt (Hamoudi and Thomas, 2014). However, once balance in the distribution of household size across treatment arms is achieved, one can safely assume that the confounding that may come from this source will be mitigated.

2.1 Methodology

Given the eligibility requirement for the OAP, the most natural way to estimate its impact is through a RD design. The fundamental assumption in our application of RD is that the probability of receiving the OAP jumps discontinuously at age 60, inducing variation in treatment assignment and this variation is unrelated to potential confounders.

We adopt the methodology introduced by Cattaneo et al (2015) for analysing RD designs. In this framework, the RD designs are analysed as a local random experiment employing a randomization inference set-up. The approach conducts an exact finite sample inference in a RD design when the sample is restricted to a small window around the cut-off where local randomization is plausible. The key assumption is that there exists a neighbourhood around the threshold where randomization-type conditions holds. As mentioned earlier, the assumption that agents are unable to manipulate their age is reasonable in our context. However, we conduct the test recommended in McCrary (2008) to verify this assumption.

The approach then proceeds by first choosing the neighbourhood or window around the threshold where treatment status is assumed to be as-if randomly assigned. This is achieved by a data-driven, randomization-based window selec-

[9] A related concern is that of manipulation of income to benefit from the grant. While this is a valid concern for the employed respondents, in the case of the unemployed, this is not a concern. Furthermore, similar to the argument for age, it is unlikely that these people will under report their income for NIDS survey. The fact that the results across employment status categories are similar suggests that the results are valid.

tion procedure that is based on balance tests of pre-treatment covariates. Once the window has been identified, established randomization inference tools are used to construct hypothesis tests, confidence intervals, and point estimates. We start by presenting the manipulation test based on density discontinuity (Cattaneo et al, 2018). This test assesses if the forcing variable satisfies the continuity condition at the threshold. Figure 1 shows the result of the test.

The conventional manipulation test statistic equals 0.24 with p-value of 0.80 and the robust statistic equals -0.98 with p-value 0.32. Since the p-values are not significant at conventional levels, we conclude that there is no statistical evidence of a systematic manipulation of the running variable.

Lastly, we present the summary statistics for the dependent variable and all the covariates for our initial sample. By this, we mean the estimation sample depends on the data driven window selection that selects the window where treatment assignment is assumed to be as-good-as randomized. The full sample includes individuals between 50 and 80 years old which satisfy the means test. Note that the estimation sample varies across the analyses and the sample size for each analysis is reported with the results.

Tables 1 and 2 show the mean and the standard deviation of individual characteristics, household characteristics and characteristics that describe the occurrence of different negative events that may affect the outcome for the employed and unemployed across treatment arms. In theory, these negative events can impact (negatively) on depression independent of the effect of income (see de Quidt & Haushofer (2017)).

Since our sample is chosen using the means test and we reckon with treatment on individual level, we did not include household level income variables as part of the covariates. Our reason for this is based on the mechanism explained by Amber (2016). What matters for individuals to exercise their personal agency (or have better bargaining power) is the income under their control and not the size of the household income. Specifically, Amber (2016) argues that it is the increase in the income share of the beneficiaries relative to what it was before that increases their bargaining power. One possible effect of this is that the beneficiaries will be able to allocate more resources to the things they care about, and by so doing lower their probability of experiencing depressive symptoms. This is because personal agency protects against depression (Cartwright et.al, 2018).

The explanation of Amber (2016) is important in understanding variation in the effect of OAP across employment status. Even though all household income variables show that comparison households have more financial resources, for beneficiaries of OAP, their share of household income increased by 22% and 18%[10] for the unemployed and employed respectively. Going by Amber (2016)'s argument, the bargaining power of beneficiaries will change in their households (perhaps more so for the unemployed) immediately they started receiving the grant. On the other hand, the bargaining power of the comparable individuals under 60 years old remains constant. The fact that the total household income

[10] For the employed (1541.67/8548.38)*100, for the unemployed (1552.02/6989.01)*100

is lower for the beneficiaries may be attributed to the retirement rate increasing as people get older than 60.

According to Nolen-Hoeksema (2001), lower level of personal agency can contribute to the development and also the maintenance of depression. In the clinical psychology literature, there is evidence that agency is related to less risk of depression in both men and women (Bandura, 2006). Therefore, an exogeneous income that increases bargaining power/autonomy/personal agency is likely to protect against depression.

As noted earlier, the randomized inference framework will mitigate the confounding that can come from other variables that are significant in Tables 1 & 2 by selecting a window within which all covariates are balanced. This balance is based on the lowest p-value of difference in means across treatment arms being above a specified threshold. In our analysis, we choose minimum p-value to be 10% , that is, in our estimation window, no variable is significantly different at the 10% level.

3 Results

Before, we present our main results, we compare depression scores across employment status and gender categories. The result is shown in table 3.

The result shows that depression scores are higher for women across all categories which is consistent with the literature (Case and Menendez, 2009). Furthermore, transitioning from comparison group to the treatment group is associated with a reduction in depression scores irrespective of the employment status and gender (note that this pattern remains even when we use CES D10 as a dummy variable, see table 3A in the appendix). However, this difference varies by gender and employment status, the largest reduction is for the unemployed men, this is followed by the employed and unemployed women respectively. These differences are significant while the difference for the employed men is small and not significant. One way to think about this result is that the categories with lower difference in depression score get the lowest benefit (in terms of depression scores) from receiving the grant. Under this logic, it makes sense that the unemployed individuals will generally benefit more since their share of the total household income is likely to increase the most. However, while this is true for men, it is not the case for women. This then suggests that while employment may protect men from depression, it does not have the same effect for women[11]. As alluded to earlier, the dual role of a bread winner and home keeper may explain this. We, however, note that this result is unconditional in that we did not control for covariates and the pattern observed may be due to selection.

Before moving to the main results, Figure 2 presents the popular RD plot (without controls). The result clearly shows a reduction in CES-D 10 score at

[11] Note that this result for the employed women disappear when CES D10 is modelled as a dummy variable.

age 60. The problem with this analysis is that the effect might be sensitive to the range of age values considered.

Using the randomization inference framework, we identify the window around the threshold where treatment status is as good as randomly assigned. If such window exists, the randomized-inference framework offers a valid alternative that minimizes extrapolation. The assumption is that because treatment assignment is as if random inside this window, the distribution of covariates unaffected by treatment outcomes should be the same between treatment and control observations.

In choosing the estimation sample, the data driven widow selection algorithm considers the variables shown in Table 1 (except household income variables and OAP amount). These variables[12] have been shown to be important correlates of depression scores. For example, Hamad et. al (2008) argue that in the case of South Africa, household size, educational attainment and gender are all correlates of CES-D scores. Note that treatment effect is given by mean difference in depression scores within the window where all other covariates are balanced i.e.

$$\tau = \frac{1}{n}\sum_{i=1}^{n} Y_i\,(1) - Y_i\,(1)\ldots\ldots 1 \tag{1}$$

where n is the number of observations in the window where randomization is plausible and $Y_i\,(T)$ represent the depression score of treated ($T = 1$) and control ($T = 0$) observations. We start by estimating the effect of OAP for the entire sample (i.e. without disaggregating by gender or employment status. Table 4 shows the result of our analysis after window selection based on the sample in Table 1.

The result shows that OAP reduces depression score (-0.847), but this effect is not significant. The sample size within the estimation window is 228, consisting of 134 treated and 91 control observations. The lowest p-value for the test of difference in means (of the covariates) within this window is 0.18. We note that the sample size is small and that may explain why the effect is not significant. The second column shows the result when the analysis is restricted to the employed individuals (without control for gender) . The result remains negative, but, insignificant at conventional levels. Next, we disaggregated the sample further by gender, that is,. the result for the employed women and men are shown in the last two columns. The result shows that despite the small sample, the effect is large and significant for the employed females, suggesting that the conclusion about the employed females based in table 3 is valid even when one controls for covariates.

In general, we exercise caution in interpreting the result in table 4 since unemployment is generally high in South Africa and this explains why the sample of the employed individuals is small (only 27% of the sample is employed)[13]. Furthermore, the sample of the employed individuals is particularly small for

[12] See description of variables in footnote of table 1.

[13] Unemployment rate in South Africa in 2017 stands at 27% see "https://data.worldbank.org/indicator/SL.UEM.TOTL.NE.ZS?locations=ZA"

the treated sample (227 observations, see table 2). However, this result consistently indicates that irrespective of the subset of observation considered, OAP reduces depression score for the employed respondents.

Table 5 presents the result for the unemployed, similar to the result for the employed population, the result is negative across all the sub-set of the population considered. However, unlike the result in table 4, the size of the estimate is larger, and the estimates are all statistically significant at 1%. While one may argue that statistical significance is driven by a larger sample size, the size of the estimate suggests that the effect of OAP in the unemployed population is larger than its effect for the employed population.

A priori one may expect that because depression is more prevalent amongst women, they should benefit more from the exogeneous income in terms of its impact on depression. While this is true across employment status for women, we note that the size of the estimate for the employed men is as high as that of the women. This suggests that perhaps the cultural/social norms that dictate that the men should be providers[14] make unemployment more detrimental for the men. Interpreted in this way, the unemployed males will be the group that should benefit more from the exogeneous income. However, this remains a question for future research.

We focus on the unemployed sample (because the sample size is larger) and consider alternative samples to show the robustness of the result.

First, we consider the possibility that some of the people who reported as being unemployed can have access to some other stream of steady income. For example, some may have retired and be collecting private pension while others may be receiving income from the Unemployment Insurance Fund (UIF). Second, since we focus on the unemployed individuals; we check the robustness of the result to the possibility that some of the individuals in our sample may have just lost their employment. To do this, we restrict the sample to those who reported as being unemployed in the current wave (wave 5) and the previous wave (wave 4)[15]. In both cases, the estimate remains negative and significant (see table 6). These results show that the effect of OAP on depression scores of the unemployed individuals in South Africa is about 1 unit and this effect is fairly robust.

4 Further Robustness checks

4.1 *Sensitivity to window length*

In this section, we present one of the sensitivity tests suggested by Cattaneo et al (2016). Similar to the last set of results, we focus on the unemployed

[14]Indeed, the difference between the mean depressions scores of the females and males is 0.66 in the population of people in employment while this figure is 1 in the population of people without employment. This suggests that unemployment might be more depressing for males because of the societal expectation.

[15]Obviously, this still leaves out the possibility that some respondents had jobs sometimes in-between the two waves (the waves are 2 years apart).

population since the sample size makes the analysis more credible. Cattaneo et al (2016) provide an algorithm that can be used to check the sensitivity of the result to different window lengths. This is important because the results in tables 4 to 6 come from various window lengths. It is therefore important to test the sensitivity of the results in table 5 to varying window lengths around the threshold. One can think of this as the confidence intervals around the treatment effect estimate for various window lengths. The result is shown in Table 7. Following the interpretation in Cattaneo et al (2016), the range of values for which the p-values are above 0.05 can be interpreted as the 95% confidence interval for the point estimate in that window. Note that the point estimates are in the first column while the window length is in the first row. The 95% confidence interval for the estimates are described by the figures shown in red in Table 7. The result shows that the confidence intervals across window lengths always include -1 which is consistent with our earlier results. It suggests that for smaller window lengths of around ± 2 years, the confidence interval includes estimates as high as -2.2. The lowest point for the lower bound of the confidence intervals across window lengths is -0.4 at window length 2.5. These results show that the estimates in Tables 5 are robust across window lengths.

4.2 *Fixed effects*

Here, we consider the possibility that individuals may vary in terms of their disposition to depression. To accommodate this possibility, we consider the fixed effects model to control for possible time invariant characteristics. To do this, we use waves 4 and 5 of the NIDS data (we clean the wave 4 data exactly the same way wave 5 data was cleaned). For this analysis, we follow Zimmerman and Katon (2005) and model CES D10 score as a count variable, therefore, we consider the fixed effect Poisson model. We also include other covariates to check how robust the result is to these covariates. Note that since we are using the full sample, the randomized inference framework is not applicable, so it is important to control for as many covariates as possible (including age which is the forcing variable for the RD design). The result is shown in Table 8

Model I in table 8 shows that although the size of the estimate is lower (one can argue that this estimate is not directly comparable with our previous results since the sample sizes are different), the effect remains negative and statistically significant (at 1%) when the covariates that were used in our previous analysis are used as controls. Furthermore, the age (model II), province and year (model III) do not change the result in any meaningful way. This result suggests that the substantive conclusion from our earlier analysis (tables 4 to 6) is valid even when we control for fixed effects[16].

[16] In the results not presented here, but, available on request, we use the pooled data, the estimate in this case is -0.511 and the estimate is significant at 1%.

4.3 *Quantile effects*

Lastly, we think of higher level of depression as a type of dis-utility, then, similar to the reason suggested for the differential impact between the males and females, those with worse depression score should experience more benefit from the OAP income. Specifically, if the same amount of exogeneous income is given to two individuals at opposite ends of the depression score scale, we will expect the impact of the income to be larger for the individual at the top end of the depression scale because they are starting from a lower base. We put this logic to a test by estimating the quantile effect of OAP on depression scores, using the jittering method suggested by Machando and Santos Silva (2005).

Similar to the analysis in section 4.2, we use a count variable model. To this end, we use the jittering method of Machando and Santos Silva (2005) to model the conditional quantile effect of OAP on depression scores. Their approach achieves smoothness in the count variable by adding a uniformly distributed noise to the count variable. This noise is constructed in a way that the resulting continuous variable have a one-to-one relationship with the conditional quantiles of the count variable. This variable can then be used to make inference on the conditional quantiles of the count data.

The result of the conditional quantile regression is shown in Figure 3. The result shows that the effect is stronger for those at higher conditional quantiles, that is,. those with very high depression score (given their covariates) experience more impact than those whose depression score is low. This shows that the significant effect observed at the mean is being driven by those with high depression scores. This suggests that proper targeting of the grant is important to get the best impact. Furthermore, it suggests that the effect of income on mental health may be heterogeneous across the distribution of depression scores.

5 Conclusion

We use a regression discontinuity design to determine that non-labour income from the South African OAP has a significant negative effect on depressive symptoms. To measure the incidence of depressive symptoms, the study uses the Centre of Epidemiologic Studies Short Depression Scale (CES-D 10). The CES-D 10 score is obtained from a 10-item questionnaire that uses a 4-point scale and ask if certain feelings or behaviour occur rarely or none of the time (assigned 1), some or little of the time (assigned 2), occasionally or a moderate amount of the time (assigned 3) or all the time (assigned 4). The aggregate responses of an individual are scored and the CES-D10 scale is the sum of the scores. We note that our estimate represents the lower bound of the effect since individuals close to the age eligibility threshold might become less depressed in anticipation of benefits receipt. Specifically, we note that for men and employed individuals, sample size might be the reason why some of the estimates for these groups turn out not to be statistically significant.

We find that this effect is larger for those whose depression score is high relative to those with low depression scores. We argue that the exogeneous income increases the ability of beneficiaries to exercise personal agency/autonomy by increasing the percentage of the household income under their control (this is especially important for unemployed individuals). The clinical psychology literature suggests that increase in personal agency can protect against depression. Although economic growth and job creation are the preferred way of alleviating unemployment and the burden it places on the population, this result suggests that the OAP provide some palliative in this respect.

We also find that the effect of OAP varies across gender and employment status. Specifically, while it appears that employment protects men against depression, our analysis suggests that it has the opposite effect for women. This suggests that the role of home keeper that women take with or without employment places more pressure on working women. This point also has implication for female headed households which has been on the increase in South Africa (Nwosu & Ndinda, 2018). An implication of this finding is that social transfers to poor households can be an effective policy in reducing depression. Lastly, we acknowledge that since the CES-D 10 score is a screening tool our results only provide an indication that exogeneous income improves mental health as measured by depression scores.=

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Table 1: Summary Statistics (Unemployed)

	Control		Treatment		t-test
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Outcome					
Depression	8.15	4.90	7.35	4.34	0.80***
Individual covariates					
Age*	55.23	3.00	68.60	5.60	-13.37***
Married	0.48	0.50	0.41	0.49	0.07***
African	0.78	0.41	0.80	0.40	-0.02
Schooling[+]	0.71	0.45	0.61	0.49	0.10***
OAP amount			1552.02	107.59	
Individual Net worth	130789.30	259896.70	116970.50	204022.80	13818.9
Female	0.70	0.46	0.70	0.46	0.003
Religious* **	0.93	0.26	0.92	0.26	0.004
Household covariates					
Household income	8423.56	18353.68	6989.01	7184.29	1434.5**
Household income (labour market)**	7486.98	8724.85	5755.07	8202.99	1731.9***
Household income (pa capita)	2297.50	5398.46	1742.79	1960.95	554.7***
Household size	5.08	2.96	5.16	3.30	-0.0753
Urban	0.52	0.50	0.41	0.49	0.103***
Dwelling type	0.82	0.39	0.82	0.38	-0.00154
Negative events					
Death of household member	0.08	0.27	0.09	0.29	-0.0136
Theft/fire destruction	0.07	0.25	0.07	0.25	0.00167
Death of livestock	0.02	0.15	0.04	0.19	-0.0152*
Crop failure	0.02	0.12	0.03	0.17	-0.0123*
Any negative event	0.01	0.08	0.01	0.11	-0.00511
No. of observations	1135		2129		

Table 2: Summary Statistics (Employed)

	Control		Treatment		t-test
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Outcome					
depression	6.82	4.43	6.04	4.62	0.784*
Individual covariates					
Age*	54.69	2.96	66.37	5.10	-11.68***
married	0.50	0.50	0.52	0.50	-0.0125
African	0.75	0.43	0.74	0.44	0.0182
Schooling+	0.63	0.48	0.65	0.48	-0.026
OAP amount			1541.67	143.06	
Individual Net worth	164044.70	306322.20	118865.10	173320.90	45179.6*
Female	0.56	0.50	0.54	0.50	0.0153
Religious***	0.93	0.26	0.93	0.25	-0.00563
Household covariates					
Household income	9607.94	11262.21	8548.38	6843.76	1059.6
Household income (labour market)**	6834.21	8744.19	4878.54	6520.48	1955.7**
Household income (pa capita)	2939.98	4564.37	2258.16	2341.11	681.8*
Household size	4.49	2.83	4.92	3.34	-0.434*
urban	0.59	0.49	0.43	0.50	0.166***
Dwelling type	0.79	0.40	0.83	0.37	-0.038
Negative events					
Death of household member	0.06	0.24	0.09	0.29	-0.0315
Theft/fire destruction	0.08	0.27	0.11	0.31	-0.0336
Death of livestock	0.03	0.18	0.11	0.31	-0.0782***
Crop failure	0.02	0.13	0.06	0.24	-0.0433***
Any negative event	0.01	0.12	0.01	0.11	0.00132
No. of observations	1032		227		

*Age (the running variable) is obtained by calculating the number of days between the birth date of the respondents and the interview date and dividing that figure by 365.25

**Household labour income is made up of fewer observation, it contains 512 and 722 observations in the control and treatment groups respectively.

Dwelling type is a variable that is equal to zero when dwelling type is "Traditional dwelling/hut/structure made of traditional materials" or "Informal dwelling/shack in backyard" or "Informal dwelling/shack not in backyard" or "Caravan/tent" or "Other (specify)" and one otherwise i.e. descent dwelling type assume the value 1.

Urban is a dummy variable that is one when the household is in an urban area

*****Religion is 1 if respondent is reported as being a member of any religious group

+Schooling dummy variable that is equal to 1 if the respondent's highest level of education is lower or equal to senior secondary

Table 3: Summary Statistic for Depression Scores across Employment Status and Gender

		treatment	control	Mean Diff	t-stat
men	**employed**	5.72	6.19	0.47	1.05
	N	104	457		
	unemployed	6.64	8.29	1.66	5.53***
	N	633	335		
women	**employed**	6.31	7.32	1.01	2.17**
	N	122	575		
	unemployed	7.65	8.09	0.44	2.12**
	N	1,495	799		

Table 4:Effect of income on depression score (All & Employed)

	All	Employed (excludes gender)	Employed (Female)	Employed (Male)
treatment effect	-0.847	-0.739	-1.779***	-0.677
effect p-value	0.177	0.227	0.01	0.620
Optimal window	[59.40 ; 60.6]	[57.75 ; 62.25]	[57.50 ; 62.5]	[59.0 ; 61.0]
covariate with min p-value	0.18	0.23	0.18	0.115
No. of observations	228	269	168	49
treated observations	134	99	108	27
control observations	94	170	59	22

Included Covariates: death of household member, theft/destruction, crop failure, any negative event, death of livestock, African, schooling, household size, urban, married, religious, gender, dwelling type, and employment status. *** $p < 0.01$. The t-test is based on 300 bootstrap replications.

Table 5:Effect of income on depression score (Unemployed)

	Unemployed (excludes gender)	Unemployed (Female)†	Unemployed (Female)‡	Unemployed (Male)
treatment effect	-1.082***	-1.091***	-1.097***	-1.611***
effect p-value	0.00	0.007	0.03	0.007
Optimal window	[55.5 ; 64.5]	[56; 64]	[57 ; 63]	[57.25 ; 62.75]
covariate with min p-value	0.129	0.105	0.119	0.151
No. of observations	1144	710	330	217
treated observations	676	433	187	126
control observations	467	276	142	91

†Note that this estimation excludes marital status, a window was not found when this variable is included. This means this result may be due to selection

‡To check the robustness of the result in the second column, the sample is restricted to the female unemployed and unmarried. The result remains negative and significant.

Included Covariates: death of household member, , theft/destruction, crop failure, any negative event, death of livestock, African, schooling, household size, urban, married, religious, and dwelling type.

*** $p < 0.01$. The t-test is based on 300 bootstrap replications.

Table 6:Effect of income on depression score for the unemployed (alternative samples)

	Exclude UIF & Private Pension	Sample with plausible persistent unemployment
treatment effect	-1.611***	-1.043 ***
effect p-value	0.007	0.000
Optimal window	[57.25; 62.75]	[55.50 ; 64.50]
covariate with min p-value	0.151	0.115
No. of observations	217	906
treated observations	91	558
control observations	126	347

Included Covariates: death of household member, , theft/destruction, crop failure, any negative event, death of livestock, African, schooling, household size, urban, married, religious, and dwelling type

*** $p < 0.01$. The t-test is based on 300 bootstrap replications.

Table 7: Sensitivity analysis

		WINDOW LENGHTS									
		1.5	**1.75**	**2**	**2.25**	**2.5**	**2.75**	**3**	**3.25**	**3.5**	**3.75**
EFFECT ESTIMATE	**-3**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	-2.8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	-2.6	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	-2.4	0.01	0.05	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	-2.2	0.02	0.12	0.06	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	-2	0.04	0.27	0.16	0.03	0.01	0.01	0.02	0.00	0.00	0.00
	-1.8	0.10	0.47	0.34	0.11	0.05	0.05	0.05	0.03	0.02	0.04
	-1.6	0.23	0.77	0.64	0.26	0.18	0.17	0.19	0.13	0.12	0.14
	-1.4	0.42	0.88	1.00	0.55	0.40	0.40	0.47	0.37	0.39	0.41
	-1.2	0.67	0.56	0.63	0.94	0.75	0.79	0.89	0.78	0.79	0.85
	-1	0.99	0.32	0.34	0.67	0.83	0.82	0.66	0.75	0.70	0.66
	-0.8	0.66	0.15	0.15	0.33	0.45	0.41	0.29	0.35	0.32	0.28
	-0.6	0.41	0.07	0.06	0.16	0.20	0.19	0.09	0.13	0.09	0.08
	-0.4	0.22	0.02	0.02	0.05	0.07	0.05	0.02	0.03	0.01	0.02
	-0.2	0.11	0.01	0.00	0.02	0.02	0.01	0.00	0.00	0.00	0.00
	0	0.03	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	0.2	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The table shows p-values that can be used to infer the confidence interval around the effect estimate for various window lengths. Values above 0.5 (in red) describe the confidence interval around the effect estimate for different window lengths.

Table 8: Marginal Effects for Fixed Effect Poisson model

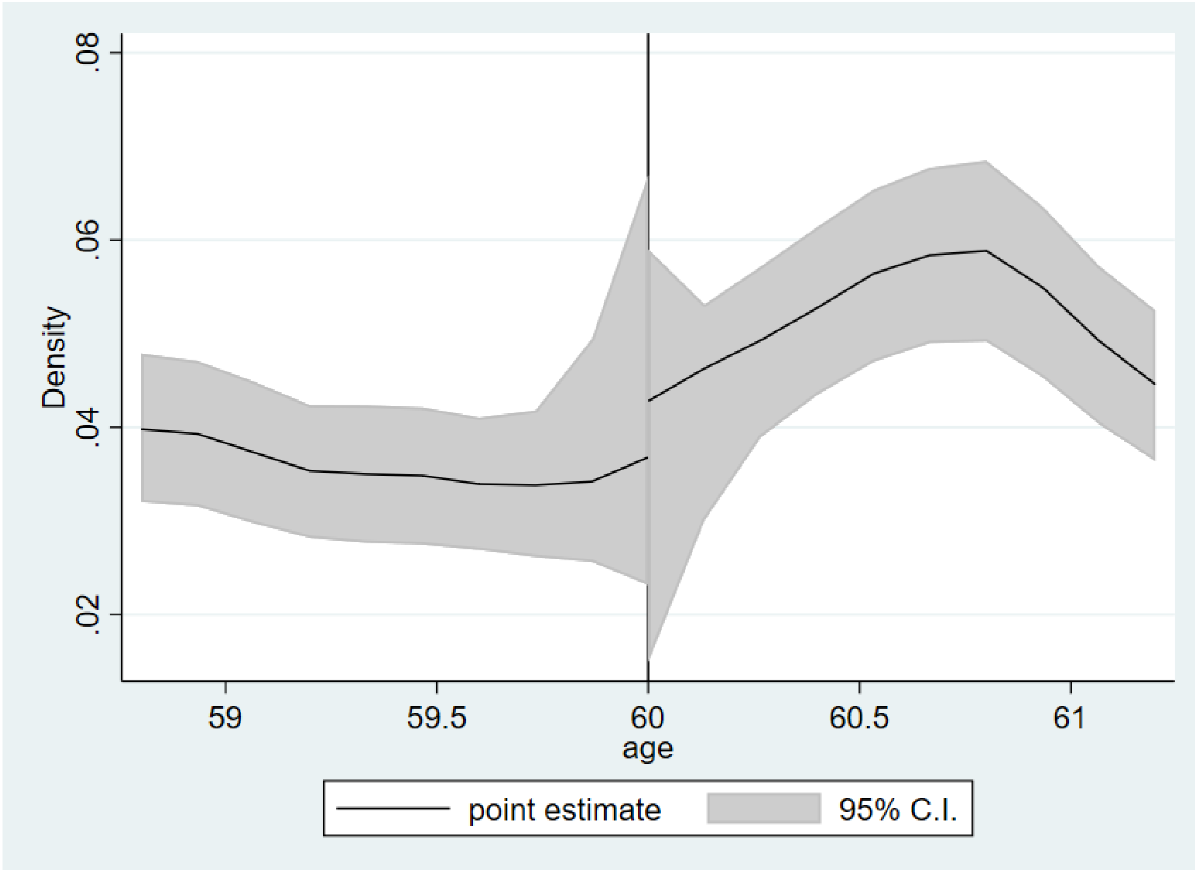
VARIABLES	(1) Marginal Effects model I	(2) Marginal Effects model II	(3) Marginal Effects model III
OAP receipt	-0.0906***	-0.101***	-0.108***
	(0.0344)	(0.0357)	(0.0359)
Death of household member	0.00794	0.00916	0.0128
	(0.0251)	(0.0251)	(0.0252)
Theft/fire destruction	0.0100	0.00946	0.00694
	(0.0282)	(0.0282)	(0.0283)
Crop failure	0.143***	0.141***	0.150***
	(0.0453)	(0.0453)	(0.0454)
Any neg event	0.0351	0.0385	0.0355
	(0.0510)	(0.0512)	(0.0512)
Death of livestock	0.128***	0.130***	0.131***
	(0.0360)	(0.0360)	(0.0361)
Schooling	0.0601	0.0598	0.0620
	(0.0545)	(0.0545)	(0.0546)
Household size	0.00648	0.00661	0.00581
	(0.00548)	(0.00548)	(0.00551)
Urban	0.0600	0.0604	-0.0355
	(0.0746)	(0.0746)	(0.0883)
Married	-0.0951**	-0.0956**	-0.0867**
	(0.0386)	(0.0387)	(0.0388)
Religion	0.0565*	0.0578**	0.0606**
	(0.0294)	(0.0295)	(0.0296)
Dwelling type	0.00655	0.00709	0.0121
	(0.0215)	(0.0216)	(0.0217)
Employment	-0.102***	-0.100***	-0.0996***
	(0.0224)	(0.0224)	(0.0226)
Age in yrs		0.00468	-0.0865***
		(0.00444)	(0.0248)
Eastern Cape+			-0.385**
			(0.192)
Northern Cape			0.482
			(0.467)
Free state			-0.444
			(0.352)
KwaZulu-natal			0.104
			(0.585)
Northwest			0.208
			(0.308)
Gauteng			-0.0993
			(0.467)
Limpopo			0.0574
			(0.356)

Wave5			0.216***
			(0.0568)
Observations	3,884	5,762	5,762

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

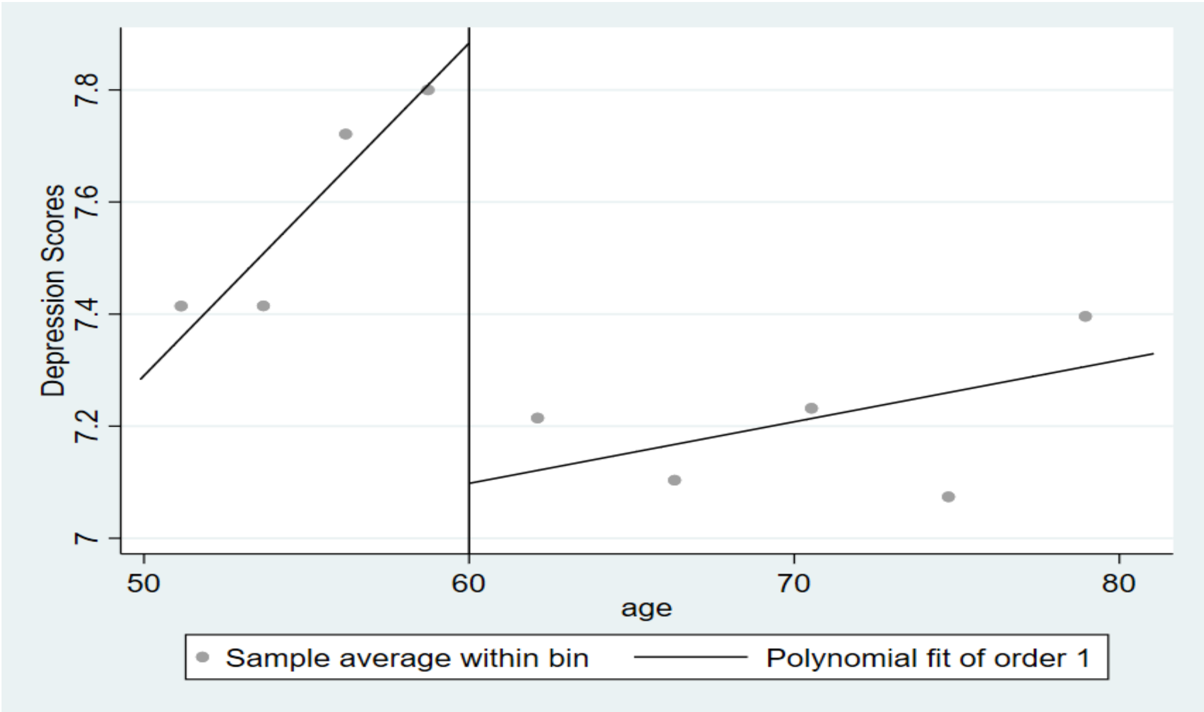
[+]The base province is western cape

Figure 1: Manipulation test result



Manipulation test result. Triangular Kernel is used, the bandwidths on either side of the threshold are 0.4. The conventional manipulation test statistic equals 0.77 with p-value of 0.43 and the robust statistic equals -0.50 with p-value 0.61. Since the p-values are not significant at conventional levels, we conclude that there is no statistical evidence of systematic manipulation of the running variable.

Figure 2: Effect of OAP on Depression Scores



The order of the polynomial used is 1, we also try the RD plot with order of polynomial 2. The result is qualitatively similar.

Figure 3: Quintile effects using the jittering method (age range 54 to 66)

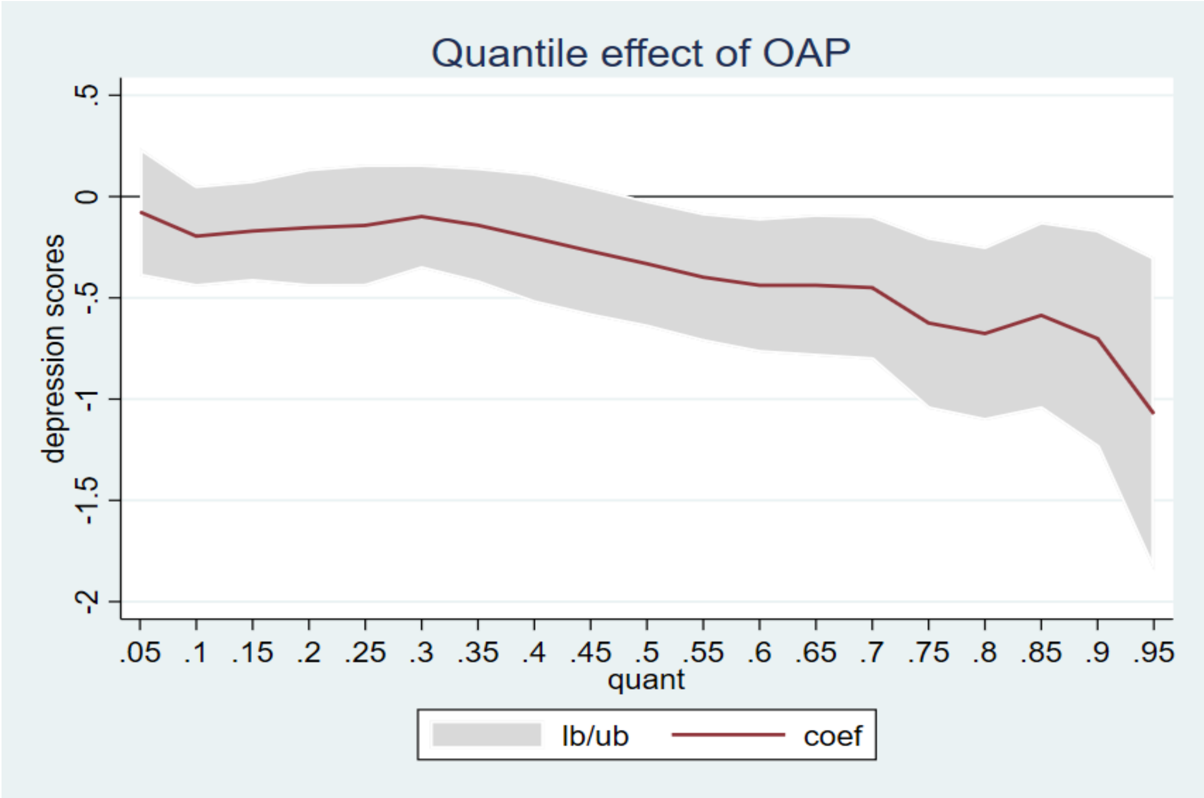


Table A1: CES-D10 Questions

Center for Epidemiologic Studies Depression Scale (Scoring)

		mean	Std Dev	min	max
1	Respondent was unusually bothered in the past week?	0.46	0.73	0	3
2	Respondent had trouble focusing in the past week?	0.55	0.77	0	3
3	Respondent felt depressed in the past week?	0.63	0.81	0	3
4	Respondent felt that everything was an effort in the past week?	0.91	1.01	0	3
5	Respondent felt hopeful about the future in the past week?	1.36	1.11	0	3
6	Respondent felt fearful in the past week?	0.45	0.70	0	3
7	Respondent's sleep was restless in the past week?	0.72	0.85	0	3
8	Respondent was happy in the past week?	1.09	1.04	0	3
9	Respondent felt lonely in the past week?	0.46	0.74	0	3
10	Respondent could not get going in the past week?	0.52	0.80	0	3

The scoring discussed is the text is adjusted as follows
Questions 5 & 8: occur rarely or none of the time (assigned 3), some or little of the time (assigned 2), occasionally or a moderate amount of the time (assigned 1) or all the time (assigned 0).

Other Questions : occur rarely or none of the time (assigned 0), some or little of the time (assigned 1), occasionally or a moderate amount of the time (assigned 2) or all the time (assigned 3).

See "https://www.brandeis.edu/roybal/docs/CESD-10_website_PDF.pdf"

Table 3A: Depression Scores as a dummy (1 if CES D10=10 and zero otherwise) across Employment Status and Gender

		dummy depression			
		treatment	control		
men	employed	0.14	0.15	0.00894	0.23
		104	457		
	unemployed	0.17	0.27	0.0997	3.67***
		633	335		
women	employed	0.19	0.24	0.0518	1.23
		122	575		
	unemployed	0.24	0.28	0.0434	2.26***
		1,495	799		