Male/Female Income and Child Growth

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Abstract

Increased male bargaining power in households causes greater expenditure on food, an improvement in Weight-for-Age Z-scores in young children, and a deterioration in Height-for-Age Z-scores in very young children, as observed in the content of South Africa's 2010 state persion expansion for males. In 2010 the male eligibility age for the South-African state pension was brought to par with female eligibility age (60, previously 65). I exploit this policy change in order to estimate the effect of the increased male bargaining power in the household, on growth of young children living in the same household, as well as food expenditure. The policy change took place shortly after the completion of the first wave of South Africa's National Income Dynamics Survey and shortly before the start of the second wave, which lends itself well for a Difference-in-Differences approach on the right hand side. On the left hand side I use z-scores of growth anthropometrics of young children in the household (against WHO standards) as well as food expenditure.

1 Introduction

In 2010 the pension eligibility age for South African males was lowered from 65 to 60 years old, at par with female eligibility. I exploit this change by estimatig a Difference-in-Differences model, quantifying the effect of increased male bargaining power in households with men aged 60 through 64. I find the following effects: increased expenditure on food, improved Weight-for-Age Z-scores (WAZ) in young children, and deteriorated Height-for-Age Z-scores (HAZ) for very young children living in the same households.

The household-as-a-unit aproach overlooks important aspects influencing the relative size of expenditure of households Thomas 1994. The lack Pareto optimal allocation of resources within households as discussed in i.a. Udry (1996); Udry et al. (1995) and Duflo and Udry (2004) indicates that this assumption in many cases, does not correspond to revealed behaviour. However, conclusive evidence on the effects of male and female bargaining within the household remains scarce.[1] In a previously study of the effects of the South-African state pension system, Duflo (2000, 2003) finds that greater female bargaining power causes improvements in anthropometic Z-scores of girls living in the same household. Unfortunately, at the time of this study in 1993, the male eligibility age was 65 and the female age was 60, while average life expentancy in South Africa then and now is significantly lower than that, making the comparison difficult.

State pension systems are a useful variable of interest to study bargaining power, since they are generally available to most citizens upon reaching a certain age. This is unlike most other sources of income, such as labour, which are almost always influenced by other demographic factors such education, place of residence, etc., which give rise to selection bias issues in the estimation.

The South African pension system is of particularl interest, because its relatively high amount, upon the initial expansion to include the black population, in 1991, this was a much as twice the mean monthly income (see Tangwe and Gutura, 2013). As a result of this, although the pension system was intended as a form of poverty relief for the elderly population, it has also become that for the South-African rural population, serving as a general source of income to many households.

In addition to this, it meets the requirements of few and simple eligibility criteria. The primary criterium is the age of the recipient. In addition to this there is a maximum income threshold, which is not met by the vast majority of the population. This relatively general applicability of the program makes that there are few selection bias issues when studying its effects. Here allowing for a clean estimation of changes in bargaining power. However, the previously-existing eligibility-age differential made it hard to make a male/female comparison, especially since average life expectancy is South Africa is substantially lower than the persion eligibility age. . For instance, one might suspect that a healthy lifestyle, which increases the chance of one becoming a pension recipient, also has an effect on the lifestyle of household members. In this is so, then our observed attrition would results in a selection bias effect. The equalising of eligibility age removes this limitation.

Child anthropometrics can be seen as a proxy for general health in the household. They are an effective way to capture both the effects of malnutrition,

[1] A further discussion of this can be found in Results.

as well as disease. Both of these factors adversely affect weight in the short run, as well as height in the long run. By comparing these anthropometrics against the international WHO standards, malnutrition and disease can hereby be captured, as well as changes herein.

The lowering of the pension eligibility age for men took place in between the first and the second wave of data collection for the South African National Income Dynamics Survey (NIDS), which took place respectively in 2008 and 2012. This survey includes data on age, state-pension eligibility and receipts, children's anthropometric z-scores, income, food/non-food expenditure, etc. The children's Z-scores are computed by comparing their anthropometics against the WHO standards.

The availability of data directly prior to and after the policy change, allow us to estimate the effect of the increased bargaining power of the newly eligible group of males aged 60 through 64 in their households using a Difference-in-Differences approach. I estimate effect of this change on food/non-food expenditure as well as on the anthropometric z-scores of young children living in the same households.

I find that the above mentioned change leads to an increase in food expenditure, but shows no significant impact on non-food expenditure. The effects on the anthropometric of children in the same households are more ambiguous. The change led to an improvement in the Weight-for-Age Z-scores, as well as a regression in the Height-for-Age z-scores of younger children.

The above results suggest that the increased expenditure in food results in improvements in the short-term Weight-for-Age indicators, but at the same time that the more long-term effect on Height-for-Age is opposite to this. A possible explanation for this is that the increase food expenditure goes towards unhealthy food, increasing weight, but not leading to any long term increases in growth.

The following section 2 discussed the National Income Dynamics Survey, as well as the WHO standards used to computer the anthropometirc Z-scores. This is followed by section 3 which discusses the empirical model estimated, as well as the tools employed for this. In section 4 I present the outcome of these estimations. Finally, in section 5 I discuss these results and their limitations, as well as some possible future directions for further research.

2 Data

The main source of data is the South African National Income Dynamics Survey (NIDS, Southern Africa Labour and Development Research Unit, 2008, 2012, 2013). Several of the dataset's key variables for this study, in turn rely on the World Health Organization's Child Growth Standards (de Onis, 2006), which are discussed at the end of this section.

The National Income Dynamics Survey of South Africa is collected by (Southern Africa Labour and Development Research Unit, 2008, 2012, 2013) in cooperation with the World Bank, it collects information on a representative set of approximately 10,000 South-African households over time. Currently three 'waves' of data are available, these waves date from 2008, 2012, and 2013. The primary types of information that I use are:

- child anthropometrics (`zwfa`, `zhfa`);

- food/non-food expenditure (`expf`, `expnf`);
- child age (`c_age_days1`);
- sex of the child (`c_woman`);
- pension eligibile adult (`man_60_65`, `woman_60_65`, `man_65`, `woman_65`).

In addition to these variables of interest, I include a number relevant of covariates, such as household income (`hhincome`), in the analysis.

In Table 2, (Table 1), and Table 3 descriptive statistics of each of the different Left-Hand Side (LHS) variables are presented. Children's anthropometrics are taken, these are length/height, weight, and waist. Using these anthropometrics and WHO growth standards, z-scores are calculated.

Table 1: Weight-for-Age z-score distributions

```
NIDS %>%
  filter(!is.na(c_woman)) %>%
  group_by(c_woman, wave) %>%
  do(tidy(summary(.$zwfa)))
```

c_woman	wave	minimum	q1	median	mean	q3	maximum	NA's
FALSE	1	-6.000	-1.194	-0.3911	-0.3405	0.4663	4.950	2390
FALSE	2	-5.830	-1.028	-0.2271	-0.2005	0.6409	4.958	2975
FALSE	3	-5.986	-1.091	-0.2732	-0.3073	0.5829	4.887	2142
TRUE	1	-5.839	-1.132	-0.3004	-0.2838	0.5024	4.951	2334
TRUE	2	-5.907	-1.097	-0.2380	-0.2246	0.6088	4.918	2922
TRUE	3	-5.615	-1.007	-0.1685	-0.1822	0.6575	4.994	2149

Table 2: Height-for-Age z-score distributions

```
NIDS %>%
  filter(!is.na(c_woman)) %>%
  group_by(c_woman, wave) %>%
  do(tidy(summary(.$zhfa)))
```

c_woman	wave	minimum	q1	median	mean	q3	maximum	NA's
FALSE	1	-5.883	-1.826	-1.0370	-1.0300	-0.25300	5.975	1135
FALSE	2	-5.993	-1.987	-1.0720	-1.1040	-0.26310	5.773	1889
FALSE	3	-5.963	-1.939	-1.0170	-1.0650	-0.17910	5.995	652
TRUE	1	-5.972	-1.696	-0.9122	-0.8742	-0.08298	5.924	1075
TRUE	2	-5.961	-1.893	-1.0020	-1.0320	-0.18450	5.875	1797
TRUE	3	-5.994	-1.847	-0.9641	-0.9827	-0.08812	5.964	634

Figure 1: Children living with a man 60-64

```
NIDS %>%
  filter( !is.na(c_woman) ) %>%
  group_by(wave, c_woman) %>%
  summarise(man_60_65=sum(man_60_65)) %>%
  ggplot(aes(x=wave, weight=man_60_65, fill=c_woman)) +
  geom_bar(position='dodge')
```

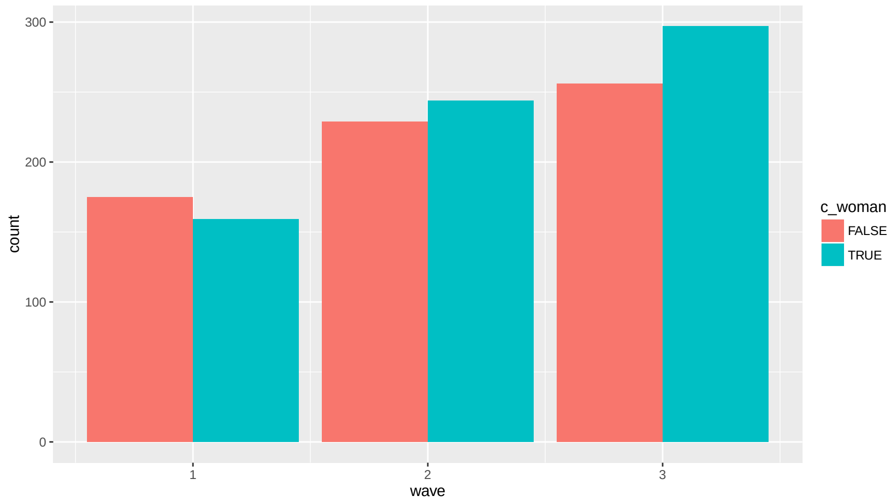


Table 3: Food expenditure

```
NIDS %>%
  group_by(wave) %>%
  do(tidy(summary(.$expf)))
```

wave	minimum	q1	median	mean	q3	maximum	NA's
1	24	500	730	947	1148	14780	NA
2	33	560	841	1015	1219	27380	1456
3	30	600	820	1061	1216	30000	944

In **??** descriptive statistics of the Right-Hand Side (RHS) variable of interest are presented. Income from the state pension system is generally the same just above 1000 SAR. I construct a dummy variable for children living in a household with a man aged 60 until 65 (`man_60_65`). As well as dummies for a man 65 years or older (`man_65`) and these same dummies for children living with women of those ages. The interaction of this dummy variable with the event dummy `post_treatment` is the variable of interest.

In addition to the explanandum, a number of relevant covariates are included in the RHS. Table 4 gives a description of the distribution of income as found in the NIDS data sets.

In 2006 the WHO published its standards for child growth(de Onis, 2006), superceding the previously used CDC Growth Charts of (Kuczmarski, 2000, CDC Growth Charts: United States). The WHO charts map the average growth of a varied sample of children living in household with healthy lifestyles, setting a sort of ideal benchmark for growth. The actual values in these of minimal importance, as long as all observations are held against the same standards the results do not differ.

Z-score anthropometrics are used since they are considered to be a good representation of a child's health, and by extension, the household in which they grow up. Z-scores refer to the practice of standardising the anthropometrics using an 'ideal' standard(de Onis, 2006).

For instance, if we measure a height x for a child of age y (in weeks/months), then we refer the to WHO tables, find the relevant ideal height and standard deviation for a child of age y. We then subtract the ideal height (μ_y) from the observed height, and divide by the standard deviation (σ_y), like so:

$$z_{xy} = \frac{x - \mu_y}{\sigma_y}$$

These ideal scores are based on a sample of children from different ethnic populations, in households which observed a healthy lifestyle. Any health issues, such as malnutrition or disease will affect these metrics, by causing the child to be shorter or lighter as compared to these ideal standards. It is however not possible to distinguish between the different causes of an observed slowed growth.

It is best practice to use only metrics for children between the ages of 6 months and 60 months.

Here we use two type of z-scores, the Height-for-Age Z-score (HAZ) and the Weight-for-Age Z-score (WAZ). Since these metrics are both age-based, they provide information about all past growth issues. Any past issues such a malnutrition and disease will have impaired growth, and these effects will still be captured by today's height. This also applies to the WAZ, as the ideal weight is a function of the height, which is in turn a function of the age.

These are constructed on a weekly basis up to the age of 60 months, and on a monthly basis thereafter.

The NIDS uses a file and data structure which is ill suited for panel data analysis. We therefore transform the data to a format which is more conducive to our analysis. In doing so, we try to stay as close as possible to the 'Tidy Data' structure, as described in Wickham (2014). In order to merge data and compute

Table 4: NIDS Income distribution

```
NIDS %>%
  group_by(wave) %>%
  do(tidy(summary(.$hhincome)))
```

wave	minimum	q1	median	mean	q3	maximum	NA's
1	0.0	1284	2165	4014	3966	130000	NA
2	100.0	1500	2583	4720	4817	446900	1089
3	126.2	1980	3376	5541	5933	300200	944

of these statistics, I make use of the dplyr and tidyr R packages Wickham (2016); Wickham and Francois (2015). After having combined the various data.frames within each wave, the three waves can be combined by simply joining the rows using base R's `rbind()` function(R Core Team, 2016).

3 Empirical methodology

This study exploits on a policy change in the South-African state pension system. Until mid 2009, men became eligible for pension at the age of 65. Between mid 2009 and December 31st 2010, this was gradually lowered to 60. I combine this information with data from the South-African National Income Dynamics Survey, a full-panel dataset, which contains information on households from before and after this policy change. I study the effect of the policy change, on the growth anthropometrics of children in the same household. The research setup in discussed in further detail below.

The identification strategy in this paper is based on a policy change in the pension eligibility age for men, which was introduced between mid 2009 and Decenber 31st 2010. This policy change thus falls between waves 1 and 2 of the NIDS, taking place between 2008 and 2012 respectively. Before this policy change, the eligibility age for men was 65 years old. Post the policy change, the eligibility age is 60 years old, which bring it at par with the pension eligibility age for women.

I operationalise this identification strategy, by constructing a policy or event dummy. This event dummy is called `post_treatment`, and takes the value `1` for data after the policy change (i.e. waves 2 & 3), and the value `0` otherwise (i.e. wave 1). By also including household income as a covaraite, I can isolate the causal bargaining effect from the income effect.

In order to identify the effect of the policy change, I employ a Difference-in-Difference estimation. This estimator operationalised by using the fixed-effects estimator. I formulate two base models. One model with the event dummy, and an interaction term with male pension recipient. The second model has the event dummy and an interaction term with the eligibility dummy, as well as interaction term with the dummies for women between 60 and 65 and women and men 65 and above.

Each of these models is estimated with both types of z-scores, as well as food and non-food expenditure as dependent variables, which gives a total of twelve estimation equations, to be estimated with random effects.

The outcome variable is y_{it}, this outcome variable takes the form of the of the z-scores, such as HAZ or WAZ or food/non-food expenditure. Here t denotes time and i the individual. The individual and time fixes effects are denoted by γ_i and λ_t respectively. Dummies for living in a household with a female or a male pension recipient are included as P_{it}^{f} and P_{it}^{m} respectively. The dummy variable T_{it} denoted the treatment status. Lastly, ϵ_{it} is the error term, which is assumed to be distributed as $\epsilon_{it} \sim N(0, \sigma)$.

$$y_{it} = \gamma_i + \lambda_t + \mu P_{it}^{f} + \nu P_{it}^{m} + X_{it} + \delta T_{it} + \rho T_{it} * P_{it}^{m} + \epsilon_{it} \tag{1}$$

As described above, I use a total of four dependent variables, Height-for-Age (HAZ), Weight-for-Age (WAZ), and food and non-food expenditure. Each of these is used in a different estimation as the Left-Hand Side (LHS) variable.

Combining these four LHSs with each of the three RHSs, gives a total of twelve estimation equations. The results of the estimation of each of these twelve equations is presented in section §section 4.

As we have only one time period before the treatment goes into effect, we cannot establish a common trend. The assumption here made is thus that the effects of P_{it}^f and P_{it}^m are level over time.

The computation estimation of these models is performed using R (R Core Team, 2016), with the implementation of the panel data structure and models using the `plm` package (Croissant and Millo, 2008).

4 Results

In Table 5, the results of the estimation using food expenditure (`expf`) as a dependent variable are presented. In ??, and ?? I present the estimation results for the age-based z-scores.

The variable `man_60_65` is a dummy variable for the child living in the same household as a male aged 60 through 64.

The other rows represent the independent variables. Where `woman_60_65` represents the dummy variable for children living in a household with a state pension eligible woman aged 60 through 64. The variables `man_65` and `woman_65` represent pension eligible men an women over the age of 65 respectively. The event variable `post_treatment` is a dummy which takes the value `TRUE` (i.e. `1`) for the data collected after the policy change, i.e. waves 2 and 3 and `FALSE` (i.e. `0`) for data collected before then. Lastly, we include the covariate `hhincome` which represents total household income.

Table 5: Food Expenditure

```
plm(expf ~      post_treatment*man_60_65 +
                man_65 +
                woman_60_65 +
                woman_65 +
                hhincome +
                woman,
                data    = NIDS,
                model   = 'random')
```

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	797.973137	10.2525018	77.8320409	0.0000000
post_treatmentTRUE	54.598225	9.1107065	5.9927542	0.0000000
man_60_65TRUE	60.992207	42.7618326	1.4263235	0.1537852
man_65TRUE	112.135045	17.8030379	6.2986466	0.0000000
woman_60_65TRUE	47.634524	16.8628202	2.8248255	0.0047337
woman_65TRUE	3.158883	13.0765143	0.2415692	0.8091156
hhincome	0.034387	0.0005494	62.5881612	0.0000000
womanTRUE	-12.610512	10.2930900	-1.2251435	0.2205306
post_treatmentTRUE:man_60_65TRUE	97.758973	48.7053825	2.0071493	0.0447426

The key result in Table 5 is the coefficient estimate for the interaction term `post_treatmentTRUE:man_60_65TRUE`, which is positive at `97.76` with a corresponding p-value of `0.04`. The coefficient estimates for the other independent variables take form as is to be expected. The estimate for household income is positive at `0.03` and highly significant at `0.00`. The parameter estimates for the other household member dummies are all positive and generally significant. The estimate for the child being a girl (`womanTRUE`) is negative at `-12.61` but not significant.

Table 6: Weight for Age

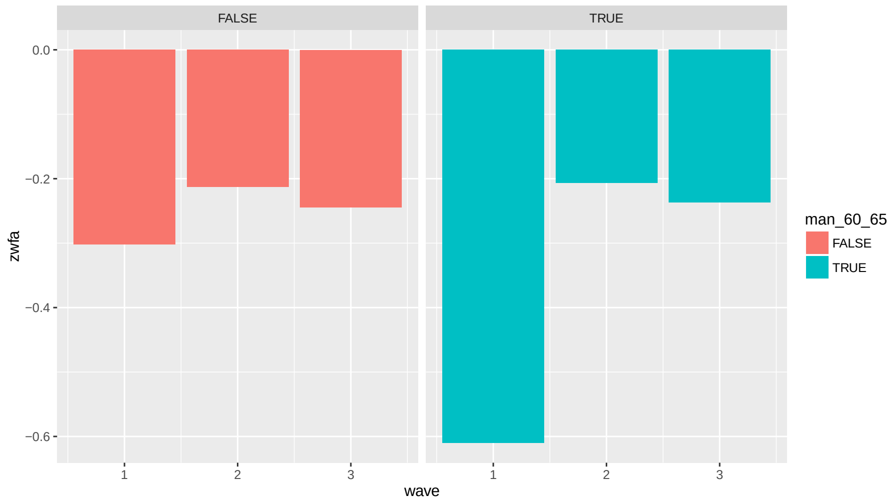
```
plm(zwfa ~      post_treatment*man_60_65 +
                post_treatment*man_65 +
                post_treatment*woman_60_65 +
                post_treatment*woman_65 +
                hhincome +
                woman,
                data = NIDS,
                subset = c_age_days1 > 180 & c_age_days1 < 2920,
                model='between')
```

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-0.3073009	0.0326055	-9.4248055	0.0000000
post_treatmentTRUE	0.0032539	0.0326791	0.0995698	0.9206876
man_60_65TRUE	-0.2768796	0.1304236	-2.1229253	0.0337810
man_65TRUE	-0.0623759	0.0854461	-0.7300029	0.4654030
woman_60_65TRUE	-0.1747761	0.0940851	-1.8576383	0.0632454
woman_65TRUE	0.0254201	0.0639132	0.3977282	0.6908378
hhincome	0.0000100	0.0000016	6.2361148	0.0000000
womanTRUE	0.0953099	0.0293109	3.2516874	0.0011505
post_treatmentTRUE:man_60_65TRUE	0.3300113	0.1479880	2.2299866	0.0257672
post_treatmentTRUE:man_65TRUE	-0.0333463	0.1008261	-0.3307311	0.7408535
post_treatmentTRUE:woman_60_65TRUE	0.1452480	0.1078110	1.3472466	0.1779269
post_treatmentTRUE:woman_65TRUE	0.0412345	0.0738919	0.5580384	0.5768288

When using Weight-for-Age (`zwfa`) as a dependent variable, the coefficient of interest is positive at `0.36` and significant, with a p-value of `0.026`. The interaction terms of the event dummy with the other household member dummies, `man_65`, `woman_60_65`, and `woman_65`, are nowhere close to significant with p-values of `0.74`, `0.18`, and `0.58`. These results can similarly be seen in Figure 2, which shows the average lag in `zwfa` for children living with a man between 60 and 65, before and after the policy change on the left, as compared to children who do not have such a household member on the right.

Figure 2: Weight for Age

```
NIDS %>%
  group_by(wave, man_60_65) %>%
  summarise( zwfa=mean(zwfa, na.rm=TRUE) ) %>%
  ggplot( aes(x=wave, y=zwfa, fill=man_60_65) ) %+%
  geom_bar(stat='identity') %+%
  facet_grid(~man_60_65)
```



When using Height-for-Age (`zhfa`) as a dependent variable to results is the opposite. I find a negative effect `-0.52` of the treatment on the dependent variable, which is just significant at a p-value of `0.09`. None of the interaction terms with any of the other household member dummies are significant, at `0.31`, `0.24`, and `0.98`.

Table 7: Height for Age

```r
plm(zhfa ~       post_treatment*man_60_65 +
                 post_treatment*man_65 +
                 post_treatment*woman_60_65 +
                 post_treatment*woman_65 +
                 hhincome +
                 woman,
                 data = NIDS,
                 subset = best_age_yrs < 4,
                 model='between')
```

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-1.3045248	0.0661855	-19.7101308	0.0000000
post_treatmentTRUE	-0.0118690	0.0722069	-0.1643745	0.8694440
man_60_65TRUE	0.1125166	0.2609687	0.4311499	0.6663809
man_65TRUE	0.1873098	0.1780119	1.0522319	0.2927522
woman_60_65TRUE	-0.3244063	0.1907804	-1.7004174	0.0891246
woman_65TRUE	0.0430632	0.1312351	0.3281375	0.7428237
hhincome	0.0000211	0.0000043	4.8737618	0.0000011
womanTRUE	0.2245553	0.0563309	3.9863642	0.0000682
post_treatmentTRUE:man_60_65TRUE	-0.5174950	0.3081696	-1.6792542	0.0931751
post_treatmentTRUE:man_65TRUE	-0.2266029	0.2252792	-1.0058756	0.3145319
post_treatmentTRUE:woman_60_65TRUE	0.2697230	0.2306746	1.1692789	0.2423560
post_treatmentTRUE:woman_65TRUE	-0.0021065	0.1644171	-0.0128120	0.9897784

As **??** and **??** show, the Weight-for-Age and the Height-for-Age estimations for all three Right-Hand Side variations give opposing results. For Height-for-Age z-scores as an explanandum, we find that the policy variable interaction term `post_treatmentTRUE:man_60_65TRUE` has a negative coefficient estimate. While this interaction term has a positive coefficient when using Weight-for-Age z-score as a dependent variable.

5 Conclusions and limitations

The estimation results present three key results. Firstly, I find that there is a significant and consistant positive effect of the interaction term (`post_treatmentTRUE:man_60_65TRUE` on food expenditure. Secondly, there is a significant and consistant positive effect of the interaction term (`post_treatmentTRUE:man_60_65TRUE` on the Weight-for-Age Z-score Thirdly, we find a consistent and negative effect of the interaction term on the Height-for-Age Z-scores. Both of these effect ae consistent across the different specifications used in our estimations.

We do this by evaluating the z-scores of anthropometrics of children between the ages of six and sixty months old, living in the same household as recipients of the South-African old-age state pension system. We then compare the z-scores for children living with male pension recipients, which the z-scores of children living with female pension recipients. This method employed here is similar to Duflo (2000, 2003), but offers some additional value. Firstly, we analyse data around a policy change, which lowers the pension eligibility age for men from 65 to 60, which brings it at par with women's pension eligibility age. There are two impeti for further analysis of this data.

Firstly, this partly overcomes major issues with attrition and the associated selection bias. Since average life expectancy is well below pension eligibility age, there is a strong indication that such a selection bias issue would be present. It is also very likely that confounding variables would be effecting both the selection bias, as well as the dependent variable. With the differential in pension eligibility age, this would make the effect incomparable, however, as the men's eligibility age is brought to the same as women's, this makes comparison less problematic. Considering the fact that selection bias in our analysis is comparable, but nevertheless still present, we note that we cannot automatically draw inferences about the external validity of the results presented here.

Secondly, analysing data around the policy change allows us to employ a Difference-in-Differences estimation (DiD). Which enables us to draw a causal inference from the treatment effect, which is ontologically more interesting than a correlation.

We use the South-African National Income Dynamics Survey data (Southern Africa Labour and Development Research Unit, 2008, 2012, 2013, jointly with The World Bank). This full-panel dataset provides observations from 2008, 2012, and 2013. The treatment, a policy change which lowers the pension eligibility age for men from 65 to 60, takes place in 2009 and 2010. Since we have only one time period before the treatment (the year 2008), we cannot establish the common trend.

In our estimations we use the Difference-in-Differences method, which is operationalised a random-effects panel estimation model. The construct two Right-Hand Side (RHS) models. The first model is a random-effects estimation with an interaction between the event dummy and a dummy for having a male aged 60 through 64 in the same household. The second model is a random-effects estimation with the same interaction, as well as an interaction terms with other dummies: `woman_60_65`, `man_65`, and `woman_65.`

On the Left-Hand Side (LHS) we use two different anthropometric z-scores, Height-for-Age (HAZ) and Weight-for-Age as well as food en non-food expenditure.

Combining the three RHS models with the four LHS z-scores gives us twelve estimation equations. In the estimation of these twelve equations, we find two effects.

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Table 8: Non-food expenditure

```
NIDS %>%
  group_by(wave) %>%
  do(tidy(summary(.$expnf)))
```

wave	minimum	q1	median	mean	q3	maximum	NA's
1	4.000	220.0	552.4	1789	1425	120300	NA
2	1.000	285.1	588.1	1678	1300	361000	1456
3	4.429	336.0	755.0	1870	1735	112000	944

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A Additional Estimates

Table 9: Non-Food Expenditure

```
plm(expnf ~       post_treatment*post_treatment +
                  man_65 +
                  wopost_treatment +
                  woman_65 +
                  hhincome +
                  woman,
                  data    = NIDS,
                  model   = 'random')
```

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	1052.4112911	56.710077	18.5577476	0.0000000
post_treatmentTRUE	-229.1189649	53.971673	-4.2451707	0.0000219
man_60_65TRUE	-12.9406582	245.515119	-0.0527082	0.9579648
man_65TRUE	-345.7800113	96.666790	-3.5770300	0.0003481
woman_60_65TRUE	-385.0294955	93.983693	-4.0967692	0.0000420
woman_65TRUE	-617.4061057	70.636448	-8.7406166	0.0000000
hhincome	0.2310988	0.003067	75.3510870	0.0000000
womanTRUE	-52.8786218	54.028761	-0.9787125	0.3277298
post_treatmentTRUE:man_60_65TRUE	-231.9316003	281.149594	-0.8249402	0.4094120

Table 10: Food Expenditure Interact All

```
plm(expf ~      post_treatment*post_treatment +
                post_treatment*man_65 +
                post_treatment*wopost_treatment +
                post_treatment*woman_65 +
                hhincome +
                woman,
                data   = NIDS,
                model  = 'random')
```

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	810.8105328	10.8755576	74.5534680	0.0000000
post_treatmentTRUE	35.2251442	10.5897866	3.3263318	0.0008810
man_60_65TRUE	55.6196875	43.0213993	1.2928377	0.1960770
man_65TRUE	112.1835241	28.5781790	3.9254959	0.0000867
woman_60_65TRUE	46.8846693	30.9664240	1.5140485	0.1300239
woman_65TRUE	-67.8984723	21.0318516	-3.2283640	0.0012463
hhincome	0.0344025	0.0005493	62.6291630	0.0000000
womanTRUE	-12.4862470	10.2886736	-1.2135915	0.2249131
post_treatmentTRUE:man_60_65TRUE	103.8232181	49.1094384	2.1141194	0.0345132
post_treatmentTRUE:man_65TRUE	0.0905759	33.1925710	0.0027288	0.9978228
post_treatmentTRUE:woman_60_65TRUE	4.6874243	35.5632106	0.1318054	0.8951391
post_treatmentTRUE:woman_65TRUE	104.2408234	24.1584808	4.3148749	0.0000160

Table 11: Non-Food Expenditure

```
plm(expnf ~     post_treatment*post_treatment +
                post_treatment*man_65 +
                post_treatment*wopost_treatment +
                post_treatment*woman_65 +
                hhincome +
                woman,
                data   = NIDS,
                model  = 'random')
```

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	1052.4112911	56.710077	18.5577476	0.0000000
post_treatmentTRUE	-229.1189649	53.971673	-4.2451707	0.0000219
man_60_65TRUE	-12.9406582	245.515119	-0.0527082	0.9579648
man_65TRUE	-345.7800113	96.666790	-3.5770300	0.0003481
woman_60_65TRUE	-385.0294955	93.983693	-4.0967692	0.0000420
woman_65TRUE	-617.4061057	70.636448	-8.7406166	0.0000000
hhincome	0.2310988	0.003067	75.3510870	0.0000000
womanTRUE	-52.8786218	54.028761	-0.9787125	0.3277298
post_treatmentTRUE:man_60_65TRUE	-231.9316003	281.149594	-0.8249402	0.4094120

Figure 3: Children living with a man 65 or over

```
NIDS %>%
  group_by(wave, man_65) %>%
  summarise( zwfa=mean(zwfa, na.rm=TRUE) ) %>%
  ggplot( aes(x=wave, y=zwfa, fill=man_65) ) %+%
  geom_bar(stat='identity') %+%
  facet_grid(~man_65)
```