Male/Female Income and Child Growth

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April 2016

Abstract

Increased in 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, 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 datasets key variable for this study, rely in turn on the World Health Organization's Child Growth Standards (de Onis, 2006), which are discussed separately in **??**.

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,;

- food/non-food expenditure;
- child age (in days);
- child sex;
- adult pension eligibility status;
- adult sex.

In addition to these variables of interest, I include a number relevant of covariates in the analysis, these are:

- household income;
- parents education.

In Table 1, (Table 2), 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: 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

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 5 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 health lifestyles, setting an 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 does 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 2: 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 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

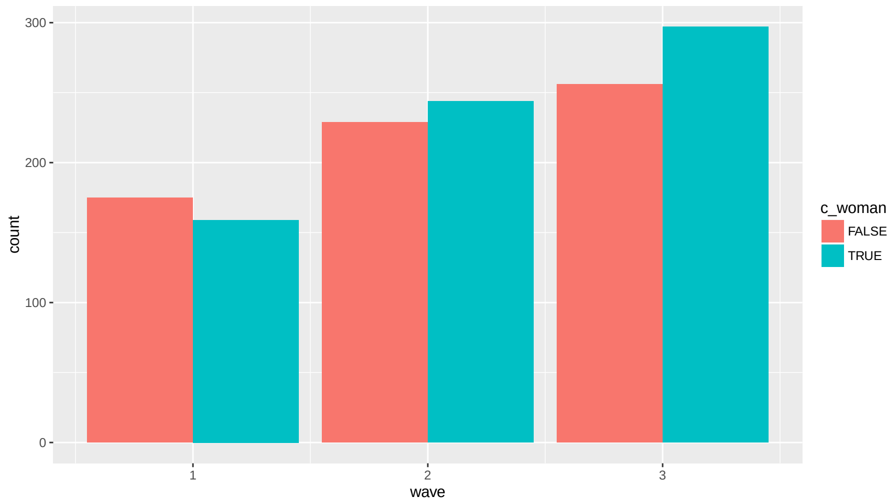
Table 4: Non-food expenditure

```
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

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')
```



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, 2013).

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 household from before and after this policy change. We study the effect of the policy change, as well as the general effect on the pension system, on the health 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 December 31st 2010. This policy change thus fall between waves 1 and 2 (2008 and 2012 respectively) of the NIDS data sets.

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 constructing a policy dummy. This policy 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).

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.

We perform these panel estimations using the R package `plm` (Croissant and Millo, 2008).

We define the variables for our estimation equations. The outcome variable is y_{it}, this outcome variable takes the form of the of the z-scores, such as HAZ or WAZ. Where t denotes the 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}

Table 5: 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

is the error term, which is assumed to be distributed as:

$$\epsilon_{it} \sim N(0, \sigma)$$

We can now formally specify our base estimations as in 1, this represents model 1.

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

In 2 we include our policy dummy variable, this variation is denoted as model 2 in our results.

$$y_{it} = \gamma_i + \lambda_t + \mu P_{it}^f + \nu P_{it}^m + X_{it} + \delta T_{it} + \epsilon_{it} \tag{2}$$

Lastly, we formulate a variant of the model which includes an interaction term of the policy dummy with the male pension-recipient dummy (as well as the variables themselves). We refer to this as model 3, and the formal specification is given in 3.

$$y_{it} = \gamma_i + \lambda_t + \mu P_{it}^f + \nu P_{it}^m + X_{it} + \delta T_{it} + \rho T_{it} * P_{it}^m + \epsilon_{it} \tag{3}$$

These three models the are variations that we use on the Right-Hand Side (RHS) of the estimation equations.

As described above, we have a total of four z-scores available as 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). 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.

4 Results

In Table 6, **??**, and **??** I present the estimation results for the age-based z-scores.

In these tables the dependent variable used it defined on the top row. The second row defines the model used (as defined in section 3). 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. The variable `man_60_65` is the dummy for the child living in the same household as a male state pension recipient. The policy variable `post_treatment` is a dummy which takes the value `1` for waves 2 and 3. An interaction term of the later two is also included as `eli.men.60:man_60_65`. Lastly, we include the covariate `w_h_tinc` which represents total household income.

Table 6: Food Expenditure

```
plm(expf ~      post_treatment*post_treatment +
                man_65 +
                wopost_treatment +
                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

As **??** and**??** shows the Height-for-Age and the Weight-for-Age estimations for all three Right-Hand Side variations give similar results. For Height-for-Age Z-scores as an explanandum, we find that the policy variable `post_treatment` has a negative coefficient estimate.

The coefficient represents the change in the expected value of a child's deviation for the standard growth anthropometics in standard deviations. A coefficient of of the dummy `post_treatment` in HAZ model 2, thus indicates that, after the lowering of the male pension eligibility age, ceteris paribus, a child's expected Height-for-Age Z-score is 0.3410 standard deviation lower than before the lowering of the eligibility age.

In **??** and **??** we do not find an effect of the `post_treatment` variable. In the WHZ estimation we do not find any significant variables. However, the BMIZ estimation we find `man_60_65` to be significant at a 5% level of all specifications.

We thus find a negative effect of the treatment on growth metrics. Furthermore, for one height-based z-score we also find a negative effect of male pension recipients on growth metrics. Additionally, it is surprising that we find significant coefficients for `man_60_65` in one height-based z-score (BMIZ), but not in the other WHZ.

The last result is surprising, in the sense that it is significant for one dependent variable, but not the other. Especially considering that the coefficient estimates for `man_60_65` in the WHZ estimations are all similar to each other, and roughly half of the estimates of the BMIZ estimations.

For the higher coefficient estimates, it is important to note that BMIZ is essentially a convex mapping of WHZ, since height is squared in the denominator of the BMI function, as described in **??**. In other words, the fact that the estimators, which give transformed coefficient estimates can have different significance levels, can be explained as follows. The squaring of the height in the denomi-

Table 7: Height for Age

```
plm(zhfa ~      post_treatment*post_treatment +
                post_treatment*man_65 +
                post_treatment*wopost_treatment +
                post_treatment*woman_65 +
                hhincome +
                woman,
                NIDS,
                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

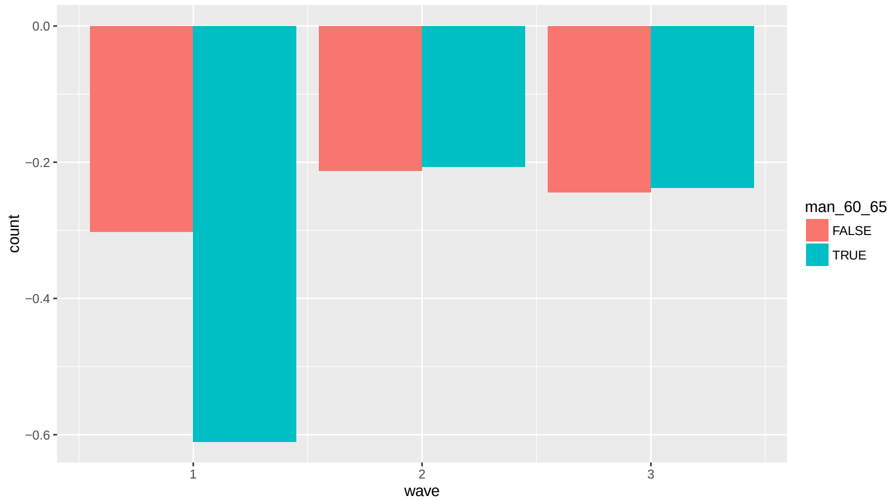
Table 8: Weight for Age

```
plm(zwfa ~      post_treatment*post_treatment +
                post_treatment*man_65 +
                post_treatment*wopost_treatment +
                post_treatment*woman_65 +
                hhincome +
                woman,
                NIDS,
                best_age_yrs < 8,
                model='between')
```

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-0.2494278	0.0218089	-11.4369487	0.0000000
spen_man_60_65	0.0000146	0.0000981	0.1486890	0.8818035
spen_man_65	-0.0001115	0.0000629	-1.7734342	0.0762024
spen_woman_60_65	0.0000226	0.0000664	0.3394649	0.7342702
spen_woman_65	0.0000447	0.0000442	1.0115180	0.3118053
hhincome	0.0000099	0.0000018	5.4121395	0.0000001

Figure 2: Weight for Age

```r
NIDS %>%
  group_by(wave, man_60_65) %>%
  summarise( zwfa=mean(zwfa, na.rm=TRUE) ) %>%
  ggplot(aes(x=wave, weight=zwfa, fill=man_60_65)) + geom_bar(position='dodge')
```



nator of the Body-Mass Index function, makes it a non-linear mapping of the Weight-for-Height Z-scores. Furthermore, from the significance at the 5% level of the coefficients in the BMIZ estimations, we can conclude that the coefficient estimates are higher that the standard error estimates, by a factor of several times (for Degrees of Freedom $\sim$ 380). Combining the small estimates of the standard errors, with the convex mapping, gives the results that the standard errors are scaled up to a lesser degree than the coefficient estimates. This then gives the results, that with t-testing the significance of the convexly mapped coefficients and standard errors, we can find significance at the 5% level for the convexly mapped BMIZ estimates of `man_60_65`, where for the WHZ estimates of `man_60_65` we could not.

Regarding the negative effect of the expansionary policy change, we need to further disseminate the change in the independent variables. **??** and **??** describe the evolution of the number of children living in a household with a pension recipient. We observe a substantial drop in both children living with male and female pension recipients. The change for the number of children living in the same household as a male pension recipient is from 612 children in 2008 to 595 children in 2012. A drop of 17 or -2.79 percent. However, if we compare the number of children living in the same household as a male pension recipient for the year 2013, the results are quite different. In the year 2013 we observe 623 children living with a male pension recipient, a rise of 1.8 percent vis-a-vis the year 2008. When comparing the number of children living in the same household as a female pension recipient, we see a different picture. In 2008 we observe 1637 children living with a female pension recipient, and in the year

2012 we observe a number of 1498, a drop of 8.49 percent. In the year 2013 we observe 1509 children living with female recipients in 2013, a drop of 8.48 oercent vis-a-vis 2008. We thus observe a drop in both the number of children living with male recipients, of children living with female recipients between the years 2008 and 2012. However, for male recipients the number rises to above 2008 levels in 2013, where as the number for female recipients remains around the lower 2012 levels.

We thus observe a drop even in the number of children living with female pension recipients, despite the fact that female pension recipients were unaffected by the policy change.

The most immediate explanation for this is the life expectancy in South Africa. Since the year 1990 the life expectancy for both women and men has consistently been dropping. The predominant reason for the this drop in life expectancy is taken to be HIV/AIDS. In **??** we plot the evolution of the life expectancy at birth in South Africa.

Around the year 2005 the life expectancy at birth was slighly above 50 years. Since pension eligibility age is 60 years (and 65 for men until 2009), there is an almost ten year gap between average life expectancy and pension eligibility. This gap causes a delayed in the effect of the drop in life expectancy. The attribition effect of a person passing away at the age of fifty, on the pension recipient base, will thus only be observed ten years after death.

After the year 2005, life expectancy started rising slowly, however, as explained above, it will take some time for this effect to appear into the pension base.

5 Conclusions and limitations

We find two results from out estimations. Firstly, we find that there is a significant and consistant negative effect of the policy variable `post_treatment` on the age-based z-scores (i.e. Height for Age and Weight for Height). Secondly, we find a consistent and negative effect of the men's pension variable (`man_60_65`) on the Body-Mass-Index Z-scores. Both of these effect are consistent across the different specifications used in our estimations.

The impetus for this paper is paper is better understanding the role that male vs. female bargaining power plays in household expenditure. A typical application of this would be Conditional or Unconditional Cash Transfer schemes (CCTs/UCTs), where the recipient of the transfer is typically the (male) head of the household, which might not be optimal under all circumstances. Which is the optimal manner in which these grants are distributed, measured along the bars of health, as well as education and work force participation. In this paper Duflo 2000, 2003 we try to address of the issue of differential effects relating to the gender of the cash recipient.

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 Bankj). 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 around 2009. Since we have only one time period before the treatment (the year 2008), we cannot establish the common trend. This common trend is used to validate the common trend assumption, which unpins the Difference-in-Differences method. As discussed in section 4, we find that not establishing the trend proves problematic for our analysis. Between the years 2008 and 2012, we see a substantial drop in the number of children living in the same household as a female pension recipient. Since female pension recipients are unaffected by the policy change, we have to assume that a further exogenous factor is the cause of this drop.

In our estimations we use the Difference-in-Differences method, which is operationalised a fixed-effect panel estimation with a time effect. The construct three Right-Hand Side (RHS) model. The first model is a fixed-effect estimation without the treatment dummy. The second model is a fixed-effects estimation with the treatment dummy (`post_treatment`). the third model is a fixed-effects estimation with the treatment dummy, as well as an interaction term with the male pension recipient dummy (`man_60_65`).

On the Left-Hand Side (LHS) we use four different anthropometric z-scores, Height-for-Age (HAZ), Weight-for-Age (WAZ), Weight-for-Height (WHZ), and BMI (BMIZ). The first two z-scores are age based (ABZ), the latter two height based (since height factors in the BMI equation, HBZ).

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.

Firstly, we find that in for both the Age-Based Z-scores (ABZs), the treatment dummy is significant for the models 2 and the models 3 (we do not find this in model 1, since it is not included the model 1 equation). In all cases, the coefficient for the treatment dummy is negative. Since both these Age-Based Z-scores (ABZs) reflect long-term or past health issues, this seems to indicate a negative correlation between the policy change on the long-term anthropometrics. Since this is the treatment dummy, this would suggest a negative causal effect of male pension receipts on child health. However, as discussed in section 4, this is likely to be a consequence of the common trend not having been established. Since we also observe a sharp drop in the number of children living with female pension recipients, despite the fact that the female pension recipient base in unaffected by the policy change.

Secondly, we find that living with male pension recipient (`man_60_65`), is negatively correlated with a the BMI z-scores (BMIZ). As discussed in section 4, the Body-Mass-Index Z-score is a convex mapping of the Weight-for-Height z-score. This can explain the fact that these essentially similar estimations, give different significance levels. Considering that the use of the Body Mass Index is far more wide spread than the Weight for Height metric, we believe that the significance of these coefficients carries more weight. The fact that these coefficients are negative, indicates that for this short-term z-score, the preferred recipient would be female household members.

In conclusion, we find a negative correlation between the treatment dummy and the long-term ABZs. This is likely to be a consequence of the common trend not having been established, since there is also a drop in the number of children living with female pension recipients, which serves as the control group. Furthermore, we find a negative correlation between the male pension recipient variable (`man_60_65`) and the short-run BMIZ.

The later result seems to indicate that, at least in the short-run, the preferred recipient of cash transfers would be a female household member. As discussed, the selection bias issue in age, leads to the need for a careful interpretation of the possible external validity of this results.q

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Table 9: Non-Food Expenditure

```r
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

A Additional Estimates

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