Grandfathers and Grandsons: Effects of a Male only Pension Change*

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Abstract

An exogenous male-only increase in cash transfer 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 context of South Africa's 2010 state pension expansion for males. When estimated separately, these effects disappear for girls, however for boys they remain intact, at a greater significance level. In 2010 the male eligibility age for the South-African state pension was brought on a par with female eligibility age (60, previously 65). I exploit this policy change in order to estimate the effects of the male-only change in cash transfers, on growth of young children living in the same household, as well as on 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 the anthropometrics status of young children in the household (against WHO standards) as well as food expenditure.

1 Introduction

Conditional Cash Transfer schemes are increasingly common in developing countries, electronic systems have made it easier to administrate these at a large schale, with lower incidences of corruption. However, the efficacy of these schemes as compared in-kind benefits such as universal health care if often brought into question, especially where the recipient of the transfer is male.

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With this study I provide a close examination of the impact of cash transfers to male household members. I examine a policy change in the South African state pension that only benefits men, bringing down the eligibility age from 65 to 60, on a par with women.

I find that this policy change leads to an increased expenditure on food, improvements in weight-for-age and a deterioration in height-for-age z-scores of young children in the household. Futhermore, when estimated separately for boys and girls, the effect for girl disappears, for boys the same effects remain intact.

The debate on CCTs and athropometric status is closely linked, malnutrition can effect physical and cognitive development, which effect future productivity and income , yet low levels of investment in Child health are often observed, despite the ineffeciency of this. On a societal level this affects i.a. growth, distribution, and welfare.

Most of the literature suggests that cash transfers to women are more beneficial to children (Thomas, 1994) . Duflo (2000, 2003) studies South African state pension shortly after the policy change that expended the system to include the black and other non-white populations in 1993. That study finds that income that acrues to a woman in the household leads to improvements in anthropometic status z-scores of girls living in the same household. At the time of this study in 1993, the male eligibility age was 65 and the female age was 60, while average life expectancy in South Africa then and now is significantly lower than that, complicating the comparison.

This age discepancy was always considered discriminatory on the basis of age. As a consequence of this, in 2010 the pension eligibility age for South African men was lowered from 65 to 60 years old, at a par with women's eligibile age. I exploit this policy change by estimating a Difference-in-Differences model, quantifying the effect of the male-only increase in cash transfers in households with men aged 60 through 64.

Although Conditional Cash Transfer schemes (CCTs) are much more common, it can be more informative to study Unconditional Cash Transfer schemes (UCTs) as these suffer less from selection bias issues. State pension systems are an opportune subject of study, since they are unconditional upon reaching a certain age.

The South African pension system is of particular interest, because of the relatively high amount of the payout, 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). Currently, the state pension payout of just over 1000 ZAR is about half of median income in South Africa. 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.

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 Study (Southern Africa Labour and Development Research Unit, 2008, 2012, 2013), which took place respectively in 2008 and 2012. This household 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 Child Growth Standards (de Onis, 2006).

The availability of data directly prior to and after the policy change, enables me to estimate the effect of the cash transfer to 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 status z-scores of young children living in the same households.

I find that the transfer 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. When I estimate these equations separately for boys and girls, the same variables have no significant effect for girls, for boys the effects remain intact, at greater significance levels.

These 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. Furthermore, the separate estimations suggest that this change only affects boys.

The following 2 discusses the National Income Dynamics Study, as well as the WHO Child Growth Standards used to compute the anthropometric z-scores. This is followed by 3 which discusses the empirical model estimated, as well as the tools employed for this. In 4, I present the outcome of these estimations. Finally, I interpret these results and their limitations in 5.

2 Data

The main source of data is the South African National Income Dynamics Study (NIDS, Southern Africa Labour and Development Research Unit, 2008, 2012, 2013), which is collected by the South African Labour and Demographics Unit together with the World Bank.

The study collects information on a representative set of approximately ten thousand South-African households over time. Currently three 'waves' of data are available, these waves date from 2008, 2011, and 2013. The key variables that I use are that I use are:

- child anthropometrics status, Weight for Age & Height for Age (`zwfa`, `zhfa`);
- food expenditure (`expf`);
- child age in days (`c_age_days1`);
- sex of the child (`woman`);
- pension eligible 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.

The child anthropometric status variables, rely on the World Health Organization's Child Growth Standards (de Onis, 2006). Children's anthropometrics including length/height, weight, and waist, are combined with the WHO growth standards, to calculate the z-scores. In table 2 andtable 1 the distributions of both variables for both boys and girls are presented. table 1 present descriptive statistics of each on the food expenditure variable.

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

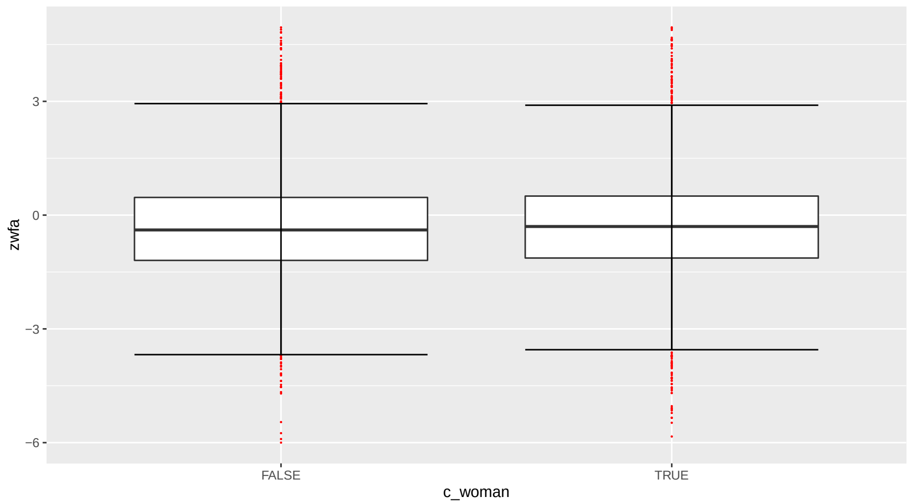


Figure 2: Height-for-Age z-score distributions

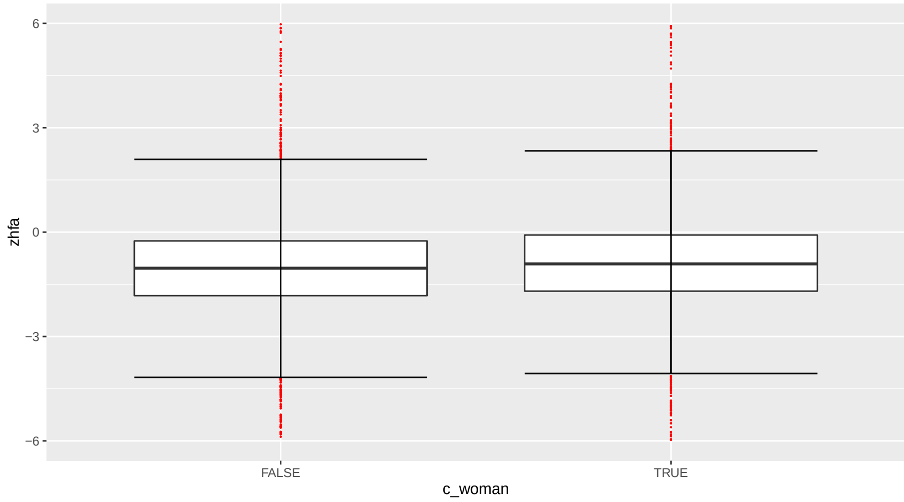


Table 1: Food expenditure

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

Income from the state pension system is generally the same at slightly more than 1000 ZAR, which is about half of median income in the data set.

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 on the RHS. table 2 gives a description of the distribution of income as found in the NIDS dataset.

Table 2: Income distribution

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

In 2006 the WHO published its standards for child growth(de Onis, 2006), superseding the previously used CDC Growth Charts of (Kuczmarski, 2000, CDC Growth Charts: United States). The WHO charts map the average growth of an ethnically varied sample of children living in households with healthy lifestyles, setting a benchmark for growth.

These z-score anthropometrics are used since they are considered to be a good representation of a child's health.

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. I therefore transform the data to a format which is more conducive to panel data analysis. For this I used 'Tidy Data' structure, as described in Wickham (2014).

3 Empirical methodology

The identification strategy in this paper is based on a policy change in the pension eligibility age for men. Until the middle of 2009, men became eligible for the state 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 Study, a full-panel dataset, which contains information on households from before and after this policy change. This policy change falls between waves 1 and 2 of the NIDS, which took place in 2008 and 2011 respectively.

I study the effect of this policy change, on the anthropometric status of children in the same household as pension recipients as well as on food and non-food expenditure.

This identification strategy is operationalised by constructing a policy change or event dummy. This event dummy is called `event`, and takes the value `1` for data after the policy change (waves 2 & 3), and the value `0` before the policy change (wave 1). This dummy is interacted with a dummy variable on having a male household member aged between 60 and 65 (`man_60_65`), as well as with dummies for men age 65 or older and dummies for women of the same ages.

In order to identify the effect of the policy change, I employ Difference-in-Differences, using the fixed-effects estimator (the Hausman test rejected random effects as biased, see section §A). Based on this setup, I formulate two base models. One model with the `event` dummy, and an interaction term with male pension recipient (`man_60_65`). The second model has the `event` dummy and an interaction term with the same `man_60_65` dummy, as well as interaction terms 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.

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

$$y_{it} = \alpha_i + \lambda_t + \delta D_{it} + \beta X_{it} + \epsilon_{it} \tag{1}$$

In this, α_i represents the individual fixed effects, λ_t represent the time fixed effects, and X_{it} are the time varying covariates. The error term is ϵ_{it}. Finally the term of interest is D_{it} .

The event variable `event` 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, I include the covariate `hhincome` which represents total household income.

As the variables of interest living with a man between 60 and 65, as well as the other household member dummy variables are determined at a household level, I apply standard error corrections to take this into account, the full procedure is outlined in section §A.

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. I present the results of the estimation in section §4.

4 Results

In table 3 I present the result of the estimations with food and non-food expenditure as dependent variables. In table 4 and table 5 I present the estimation results for the equations with anthropometric status as the dependent variables. The first four items in each table represent the interaction terms between the event dummy and the various household member dummies, e.g. the variable `man_60_65` is a dummy variable for the child living in the same household as a male aged 60 until 65.

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 until 65. The variables `man_65` and `woman_65` represent pension eligible men an women over the age of 65 respectively.

As mentioned in section §3 I estimate the equations using only the interaction term with man_60_65 as well as with all household member of age dummies, such as woman_65, etc. I only present the results here using all interaction terms. The estimates with the sole interaction term are qualitatively and quantitatively similar to the full estimates and are available in section §A.

Table 3: Food and Non-Food Expenditure

	Food	$(P > \|t\|)$	Non-Food	$(P > \|t\|)$
event * Man 60-65	**103.82**	(0.03)	-0.05	(0.22)
event * Man 65+	0.09	(1.00)	-0.02	(0.35)
event * Woman 60-65	4.69	(0.90)	0.02	(0.36)
event * Woman 65+	**104.24**	(0.00)	0.01	(0.51)
Man 60-65	55.61	(0.20)	206.16	(0.57)
Man 65+	**112.18**	(0.00)	377.43	(0.57)
Woman 60-65	46.88	(0.13)	-356.02	(0.16)
Woman 65+	**-0.68**	(0.00)	-181.57	(0.38)
event	35.23	(0.00)	131.32	(0.08)
Household Income	**0.03**	(0.00)	**0.09**	(0.00)
Girl	-12.49	(0.22)		
Intercept	**810.81**	(0.00)		
Observations	15938		15938	

The key result in 3 is the coefficient estimate for the interaction term event * man_60_65, which is positive at 103.82 with a corresponding p-value of 0.03. This coefficient estimate represents a 103.82 Rand (ZAR) increase on food expenditure in the households which received the additional income through pension receipts of men aged between 60 and 65.

The coefficient estimates for the other independent variables expected forms. The estimate for household income is positive at 0.03 and highly significant at 0.00.

Table 4: Weight for Age

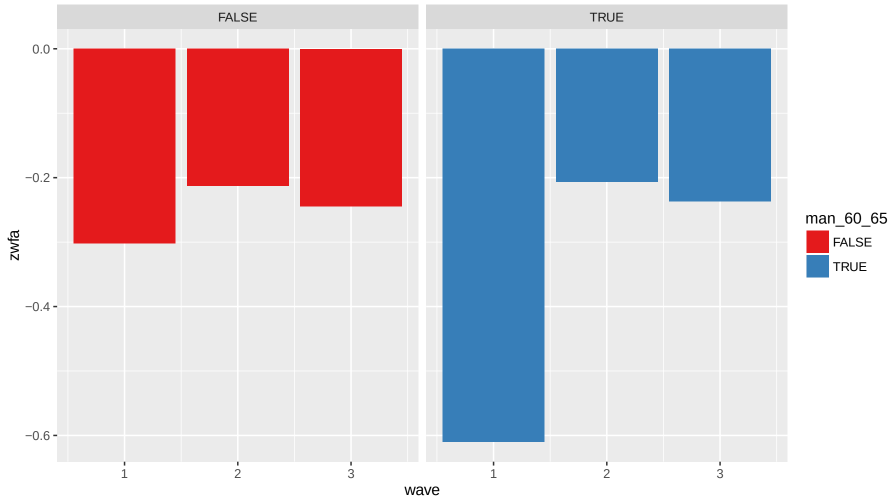
	General	$(P > \|t\|)$	Boys	$(P > \|t\|)$	Girls	$(P > \|t\|)$
event * Man 60-65	**0.33**	(0.02)	**0.44**	(0.03)	0.26	(0.23)
event * Man 65+	-0.03	(0.74)	0.15	(0.31)	**-0.30**	(0.05)
event * Woman 60-65	0.15	(0.18)	0.18	(0.23)	0.13	(0.44)
event * Woman 65+	0.04	(0.58)	0.29	(0.79)	0.03	(0.77)
Man 60-65	**-0.27**	(0.03)	**-0.35**	(0.06)	-0.29	(0.13)
Man 65+	-0.06	(0.47)	**-0.35**	(0.01)	**0.26**	(0.04)
Woman 60-65	**-0.17**	(0.06)	-0.14	(0.27)	-0.18	(0.21)
Woman 65+	0.03	(0.69)	0.09	(0.32)	-0.02	(0.80)
event	**0.00**	(0.00)	0.01	(0.85)	0.06	(0.19)
Household Income	**0.00**	(0.00)	**0.00**	(0.00)	0.00	(0.00)
Girl	**0.09**	(0.00)				
Intercept	**-0.31**	(0.00)	**-0.33**	(0.00)	**-0.23**	(0.00)
Observations	11740		5878		5862	

When using Weight-for-Age as a dependent variable, the coefficient of interest is positive at 0.33 and significant, with a p-value of 0.02. This respresents an increase of 33% of a standard deviation of the WHO Child Growth Standards towards the WHO target mean value.

The interaction terms of the event dummy with the other household member dummies, `man_65`, `woman_60_65`, and `woman_65`, are not significant with p-values of 0.74, 0.18, and 0.58 respectively. A graphical illustration of this result can be seen in figure 3, 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.

I also estimate this equation separately for boys and for girls. The estimation including only boys gives a somewhat higher estimate of 0.44, with a p-value of 0.03. The estimate for girls is lower at 0.26 and insignificant at a p-value of 0.23.

Figure 3: Weight for Age



When I use Height-for-Age as a dependent variable to result found is the opposite. I find a negative effect -0.52 of the treatment on the dependent variable, at a p-value of 0.09. This represents a drop of 52% of a standard deviation in the WHO Child Growth Standards, falling futher below the WHO target mean value.

None of the interaction terms with any of the other household member dummies are significant, at p-values of 0.31, 0.24, and 0.98 respectively. When I reestimate the equation to only include boys in the sample, I find a much greater effect of -0.94, which is also more significant, at a p-value of 0.04. The same is not true of the restimation which only includes girls, where the estimate is -0.24 and entirely insignificant at a p-value of 0.57.

The coefficient estimate for Girl is 0.09, which means that on average across all three waves, girls z-scores are 9% of a WHO standard deviation less below the WHO target mean value than boys are.

The value of the household income coefficient is very low (rounded to 0.00) but highly significant at a p-value of 0.00, this is simply because the margin effect of one additional Rand is very small but nevertheless decisively positive.

Table 5: Height for Age

	General	(P > |t|)	Boys	(P > |t|)	Girls	(P > |t|)
event * Man 60-65	**-0.52**	(0.09)	**-0.94**	(0.04)	-0.24	(0.57)
event * Man 65+	-0.23	(0.31)	-0.03	(0.92)	-0.36	(0.25)
event * Woman 60-65	0.27	(0.24)	0.55	(0.08)	0.02	(0.95)
event * Woman 65+	-0.00	(0.98)	-0.16	(0.49)	0.14	(0.54)
Man 60-65	0.11	(0.66)	0.35	0.37	-0.06	(0.85)
Man 65+	0.19	(0.29)	-0.07	(0.79)	0.42	(0.08)
Woman 60-65	**-0.32**	(0.08)	-0.26	(0.32)	-0.40	(0.15)
Woman 65+	0.04	(0.74)	0.12	(0.50)	-0.03	(0.88)
event	-0.01	(0.867)	0.01	(0.92)	-0.03	(0.77)
Household Income	**0.00**	(0.00)	0.00	(0.00)	**0.00**	(0.00)
Girl	**0.22**	(0.00)				
Intercept	**-1.30**	(0.00)	**-1.30**	(0.00)	**-1.08**	(0.00)
Observations	4809		2301		2377	

5 Conclusions and limitations

The impetus for this paper is to gain a greater understanding of the efficiency of cash transfers to male household members, to for instance improve the designs of CCTs.

I analyse data from the National Income Dynamics Study around a lowering of the pension eligibility age for men, from 65 to 60, in the South African state pension system.

Using a Difference-in-Differences based identification strategy, I compare differences in the anthropometric status of children living in the same household as men of the newly eligible age.

On the Right-Hand Side I use a dummy variable for the policy change as well as dummy variables for men aged 60-65, men age 65+ and the same ones for women as household members. On the Left-Hand Side (LHS) I use two different anthropometric z-scores, Height-for-Age (HAZ) and Weight-for-Age as well as food en non-food expenditure. In addition to the general estimates using z-scores as a dependent variable, I also reestimate these two equations once using only boys in sample and once using only girls.

The estimation of these equations gives three key results. Firstly, I find that there is a significant and consistent positive effect of the interaction term of the event dummy and the man_60_65 dummy, on food expenditure. Secondly, there is a significant and consistent positive effect of the same interaction term on the Weight-for-Age Z-score, the interaction terms with other household member dummies are not significant. Thirdly, I find a consistent and negative effect of the interaction term on the Height-for-Age Z-scores. All of these effect are consistent across the different specifications as well as standard error corrections.

These effects suggest that the male income resulted in greater food expenditure, which improved the Weight-for-Height anthropometric status. Since the estimation includes data from two waves after the policy change, we would expect this additional food expenditure to also lead to an improvement in the more long-term metric of Height-for-Age. Surprisingly we observe an opposite effect here. An explation for this could be that nature of the expenditure on food has changed, helping improve the Weight-for-Age, but not improving the Height-for-Age, with the later being a more long term health indicator.

When I subset to a data to only includes girls and reestimate the equation with the two z-score dependent variables, I find no significant effects. However, using a subset of only boys gives the same results as in the original estimation and at greater significance levels. This makes it unlikely that the surprising deterioration in Height-for-Age can be attributed to another factor such as the 2008 global financial crisis, since this would in all likelyhood also have affected girls as it did boys.

More central to this study, it suggest that the cash transfer only affected boys living with a new recipient. As shown in table 1, the boys in the dataset scored slightly worse in the Weight-for-Height z-scores. One possible explanation for the improvement in Weight-for-Age in boys could be that they benefitted more in terms of this metric because they were behind more. However, this is at odds with the detioration in Height-for-Age, since also here, boys scored worse even in wave 1 of the dataset. Should a greater lag have been the cause of the effect in the improvement in Weight-for-Height then we would expect a similar improvement in Height-for-Age.

An alternative explanation could be that if the cash transfer was used to purchase unhealthy food, which increases weight but is not nutritious in terms of promoting growth, than this was only spent on boys in the household. If there is merit to this last explanation, then this result mirrors the result found in Duflo (2000, 2003), where the central result is an improvement in girls anthropometric status when they live with a female pension recipient.

The first key outcome of this research is that food expenditure is some way too ambiguous a variable. The results of the increased food expenditure are not altogether positive, leading to a deterioration in Height-for-Age. In context such as these, the increased food expenditure would generally be thought of as a positive development. By further analysing the types of food purchased, it might be possible to better understand the deterioration in Height-for-Age.

The second key outcome of this research is that both the positive and negative consequence of the male-only cash transfer seem to only effect boys. This could suggest that, similarly to Duflo (2000, 2003) the grandparent seems to spend only on grandchildren of the same sex.

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A Additional Estimates

Table 6: Standard Error Correction

```r
library(lmtest)   # standard error correction
library(broom)    # output formatting

# standard error correction
tidy( coeftest(expf1, vcov=vcovHC(expf1,
                                  type="HC0",
                                  cluster="group")) )
```

term	estimate	std.error	statistic	p.value
(Intercept)	797.973137	20.4834004	38.957064	0.0000000
post_treatmentTRUE	54.598225	9.4195865	5.796244	0.0000000
man_60_65TRUE	60.992207	30.8335999	1.978109	0.0479254
man_65TRUE	112.135045	19.9611804	5.617656	0.0000000
woman_60_65TRUE	47.634524	15.3353771	3.106185	0.0018969
woman_65TRUE	3.158883	12.1322850	0.260370	0.7945802
hhincome	0.034387	0.0047316	7.267585	0.0000000
womanTRUE	-12.610512	10.1037207	-1.248106	0.2120019
post_treatmentTRUE:man_60_65TRUE	97.758973	39.4529129	2.477864	0.0132225

Table 7: 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

Table 8: 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 9: 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   = 'within')
```

	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 10: Girls Height for Age

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

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-1.0827829	0.0853476	-12.6867426	0.0000000
eventTRUE	-0.0292989	0.1014385	-0.2888346	0.7727352
man_60_65TRUE	-0.0656365	0.3501531	-0.1874508	0.8513245
man_65TRUE	0.4217243	0.2468947	1.7081136	0.0877565
woman_60_65TRUE	-0.3987542	0.2798468	-1.4249014	0.1543277
woman_65TRUE	-0.0273289	0.1885614	-0.1449338	0.8847765
hhincome	0.0000250	0.0000058	4.3324668	0.0000154
eventTRUE:man_60_65TRUE	-0.2353016	0.4120205	-0.5710920	0.5679957
eventTRUE:man_65TRUE	-0.3603559	0.3146522	-1.1452513	0.2522298
eventTRUE:woman_60_65TRUE	0.0214524	0.3339310	0.0642420	0.9487834
eventTRUE:woman_65TRUE	0.1394328	0.2329406	0.5985769	0.5495168

Table 11: Boys Height for Age

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

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-1.2998129	0.0848152	-15.3252272	0.0000000
eventTRUE	0.0103725	0.1028205	0.1008795	0.9196557
man_60_65TRUE	0.3491800	0.3913368	0.8922751	0.3723477
man_65TRUE	-0.0665181	0.2569582	-0.2588674	0.7957629
woman_60_65TRUE	-0.2599733	0.2609596	-0.9962203	0.3192579
woman_65TRUE	0.1223980	0.1829573	0.6689976	0.5035705
hhincome	0.0000156	0.0000065	2.3876923	0.0170425
eventTRUE:man_60_65TRUE	-0.9431906	0.4647851	-2.0293047	0.0425532
eventTRUE:man_65TRUE	-0.0319730	0.3231811	-0.0989320	0.9212017
eventTRUE:woman_60_65TRUE	0.5501036	0.3207639	1.7149798	0.0864965
eventTRUE:woman_65TRUE	-0.1619634	0.2326134	-0.6962771	0.4863324

Table 12: Height for Age

```
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

Table 13: 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

Table 14: Food Expenditure

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

	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 15: Hausmann

```
model_expf2 <- expnf ~ post_treatment*man_60_65 +
post_treatment*man_65 +
woman_60_65*post_treatment +
post_treatment*woman_65 +
hhincome +
woman

fe_expf2 <- plm(model_expf2, data=NIDS, model='within')

## series fwag, cwag, swag, chld, fost, spen_flg, ppen_flg, uif, remt are NA and have been
## series spen, ppen are constants and have been removed

re_expf2 <- plm(model_expf2, data=NIDS, model='random')

## series fwag, cwag, swag, chld, fost, spen_flg, ppen_flg, uif, remt are NA and have been
## series spen, ppen are constants and have been removed

phtest(fe_expf2, re_expf2)

##
##  Hausman Test
##
## data:  model_expf2
## chisq = 857.92, df = 10, p-value < 2.2e-16
## alternative hypothesis: one model is inconsistent
```

B Software

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 by Croissant and Millo (2008). Generalized Linear Models for the panel data set are estimated using the pglm package by Croissant (2013).

All changes are logged using the version control system Git (**git**) and publicly available on GitHub at https://github.com/bquast/MaleFemale-Bargaining-Power-Child-Growth/[1].

In order to merge data and compute 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).

[1]The repository can by cloned to a local computer by entering in following command in a terminal (with Git installed):
`git clone https://github.com/bquast/MaleFemale-Bargaining-Power-Child-Growth.git`