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Supplementary Information for

Assessing multi-dimensional sustainability: lessons from Brazil's social protection programs

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Supplementary Information Text

Materials

Unit of Analysis. We compile data at the municipality level, i.e. Brazil's lowest administrative unit. We confine analyses to rural municipalities because ZH policies implemented in rural and urban areas differ in their implementation, mechanisms, and effectiveness (1, 2), and because small rural farmers are vital for national food security. Small farmers produce 70% of the food consumed in Brazil but also suffer disproportionately from food insecurity (2). We use the OECD definition of urbanisation, excluding municipalities with human population densities above 150 inhabitants/km² (3), as the official Brazilian definition overestimates the distribution of urban areas (4).

During our study period 41 municipalities split into two or more municipalities. In these cases, we recalculate data for the end of the study period to match the original municipality boundaries at the start of the study period using two approaches. If data were available for each of the new municipalities we summed these and then recalculated data based on the older municipality boundaries. Alternatively we calculated weighted means based on municipality area for average slope, average elevation, and drought incidence; and by population size for census derived infant mortality and life expectancy. Municipalities which merged during our study period (four for the 2004-2013 analyses and 45 for the 2000-2010 analyses) had to be excluded because the change in municipality borders (multiple municipalities merged to create single municipalities) were such that 2010 or 2013 (endpoint) values could not be accurately assigned baseline values. See Table S10 for more details of specific model exclusions and Table S1 for final sample sizes.

Outcome variables. We use eight response variables to cover key dimensions of food availability, multi-dimensional poverty, health and natural vegetation loss. Our models include values at the start of program implementation to control for baseline conditions.

Food production. We use daily per capita kilocalorie and protein production. We use these two measures to make a distinction between food quantity (kilocalories) and food quality (protein) (5). Both measures are based on annual municipal agricultural production data from the national statistics office IBGE (6). We combine twelve main Brazilian agricultural products, and convert each quantity produced (kg/tonnes) into kilocalorie and protein metrics using standard Brazilian and/or US product macronutrient/food energy values (7, 8). We use the average of these two values when both are available (Table S5). We then convert to daily per capita values based on the municipality's population size in the focal year (using data from IBGE: https://www.ibge.gov.br/). The agricultural data does not include subsistence food production, but this is a small and declining proportion of total production due to the shift towards a more modernized market oriented agricultural systems (9).

Multi-dimensional poverty (MPI). We use data from the 2000 and 2010 demographic census to generate a multi-dimensional poverty measure, which we refer to as multi-dimensional poverty (census). Our measure combines equally weighted data on health, education, and living standards based on the recommendations of Alkire and Foster (10). Because household-level data are not available as part of the census micro-data, we use the geometric mean from all census households to generate our combined multi-dimensional poverty measure. This general approach follows the method used to calculate Brazil's official Municipal Human Development Index (MHDI) (11), which is closely correlated with our measure (r = 0.90 and 0.84 for 2000 and 2010, respectively), despite the underlying dimensions being somewhat different. We do not, for instance, include a financial income variable and rather include information on living standards given it is a more direct measure of deprivation of capabilities in line with the rationale of the MPI (10). For the education dimension we focus solely on primary and lower secondary school attendance, which is compulsory in Brazil, as this is a main focus of ZH programs (9). Fig. S3 illustrates relationships between the multi-dimensional poverty (census) and MHDI dimensions. Whilst the need to use the geometric mean (due to data availability) prevents us from assessing changes in the number of people below set poverty thresholds (10), our index provides a strong indicator of temporal change in multi-dimensional poverty. In addition, we use data from the Brazilian National Primary Information System (SIAB) for 2004 and 2013 (12), which we refer to as multi-dimensional poverty (SIAB) to assess multi-dimensional poverty change in the poorer sectors of society. SIAB contains information for all families targeted by The Family Health Program. This is the national decentralised primary health care program aimed at providing health care coverage especially in deprived areas (13). The multi-dimensional poverty (SIAB) measure combines equally weighted data on health, education, and living standards but uses slightly different variables for each dimension than those used by multi-dimensional poverty (census) due to differences in primary data collection (see Table S6). Our two poverty measures are thus related but not directly equivalent.

Child malnutrition and infant mortality. We use child malnutrition and infant mortality as measures of food insecurity and health (14). Our measures of infant mortality are derived from both the national census and SIAB. The national census does not include child malnutrition measure and these data are derived solely from SIAB. Our malnutrition data combines data on underweight new-borns and underweight children (between 12 and 24 months). We combine these two measures using the geometric mean. We avoid double counting children weighed more than once at age one by selecting records for only four months a year, selecting the two wettest and two driest months per municipality per year to avoid a temporal bias, based on fine-scale monthly municipal rainfall data (15). Our measure of infant mortality is the number of annual infant deaths (children <1 year) per 100,000 live births. We use data from both SIAB and the national demographic census as this allows us to consider infant mortality both in poorer sectors of society, and the entire municipal population. We define child malnutrition per 10,000 children, and infant mortality per 100,000 live births, rather than the more standard per 1,000 and 100, respectively, in order to retain more information when modelled using a Poisson modelling framework which does not allow decimal values.

Natural vegetation cover. We use a 30m resolution Landsat-derived remote sensing product published by *The Brazilian Annual Land Use and Land Cover Mapping Project v2* (16). Our measure focuses specifically on natural vegetation change for each of the six Brazilian biomes (Amazon rainforest, Cerrado, Caatinga, Pantanal, Atlantic Forest, and Pampa). The MapBiomas dataset maps vegetation cover according to 28 vegetation classes: we use 12 classes to construct our area under natural vegetation (Table S7). We calculate area of natural vegetation in each municipality and validate these estimates by comparison with alternative datasets, i.e. Terra Class for the Amazon and Cerrado, PMDBBS for the Caatinga and Cerrado, and SOS Atlantic Forest (Table S8). We only consider pixels that have been observed in both years and also ensure that the majority of each municipality in the analysis is consistently observed by excluding 17 municipalities where less than 50% of the total area was observed in either 2004 or 2013 due to cloud cover. As a robustness test we also consider a more stringent threshold and exclude municipalities with >5% cloud cover in either 2004 or 2013.

Treatment variables - ZH policy implementation. We use data on annual municipal investments obtained via government managed online platforms (www.dados.gov.br and www.mds.gov.br) of the four main ZH sub-programs: PRONAF, PAA, PNAE and BF. All four sub-programs grew steadily since inception (Fig. S4), and show large spatial variation in investment across Brazil (Fig. S1). We exclude other minor sub-programs because they lack data at a municipal level and are much more limited in geographical spread. Information on the number of beneficiaries is publicly available for some ZH sub-programs, but this variable is not defined in a consistent way as one beneficiary could represent one individual, one co-operative that contains multiple farmers (but an unknown number of farmers or people) or one family that contains an unknown number of family members. It is thus impossible to use such data to capture the number of individuals in a municipality targeted by the ZH program or its sub-programs. A financial value capturing ZH program investment is thus more appropriate for quantifying spatial variation in investment.

We measure ZH investment as the summed per capita financial investment allocated to each municipality from the four sub-programs between 2004 and 2013. The ZH program was officially launched in 2003. However, we focus the majority of our analysis from 2004 onwards because investment levels in the program's first year were small (17, 18) and major changes to ZH's largest sub-program, BF, were implemented in 2004 (19). PAA investment is included from 2006 onwards (inclusive) due to insufficient data availability but investment prior to 2006 was minimal (Fig. S4). For analyses using outcome variables spanning 2000 to 2010, we match investment to the same time frame and measure ZH as summed ZH sub-program investment from 2000 to 2010. Investment values are expressed as 2013 values (in units of R$1000 per capita; using population data from IBGE) using Brazil's inflation index IGP-DI.

Confounding variables. We extract data on 15 biophysical and socio-economic factors that are used to calculate covariate balance generalized propensity scores and thus limit potential non-random treatment allocation bias by reducing the correlation between treatment and potential confounding factors. The variables are also used as control variables in our regression models. Here we describe each variable and the rationale for inclusion.

i) Total municipal area. Administrative area can significantly influence social and environmental outcomes in impact estimation studies (20), and has been linked to implementation efficiency of BF (21). Municipal area data are taken from IBGE (https://www.ibge.gov.br/).

ii) States. States in Brazil have substantial decision-making power, heterogeneous economies, and receive different amounts of federal financial support (9) which could influence the effectiveness of ZH investment.

iii) Ecological biome. Brazil can be divided into six ecologically distinct biomes (Amazon rainforest, Cerrado, Caatinga, Pantanal, Atlantic Forest, and Pampa). These differ substantially in ecological and biophysical conditions and degree of protection (22), with significant implications for agricultural production and rural livelihoods and interpretation of the effects of natural vegetation loss. We calculate the percentage land cover of each biome within each municipality using official biome boundaries (23). When using biome as a predictor in models of food security, health and multi-dimensional poverty outcomes we assign a specific biome to each municipality if $\geq$ 80% of a municipality's area falls within a single biome, and assign each of the 253 municipalities that did not meet this criterion to one of seven transition categories (e.g. Cerrado/Atlantic forest) creating a 13 level factor (Biome 13cat). When modelling natural vegetation we classified each municipality as the biome which comprised the majority of land cover (creating a 6 level factor; Biome 6cat) as use of the transition categories adversely affected model convergence.

iv) Population density. Population pressure is a key driver of land-use change and can have substantial effects on land-use practices, access to resources and ultimately, livelihoods (24). We measure baseline population density using population estimates and municipal area data from IBGE.

v) GDP per capita from public services. Financial support for local institutions can have substantial effect on livelihoods and wellbeing. We measure baseline levels of per capita municipal spending on public administration including areas of health, education and social security (25). We deflate these values relative to 2013, expressed per capita (in R$1,000 units) using population data from IBGE.

vi) Electoral patterns.

Electoral patterns can influence public spending (26–28), and thus influence our treatment allocation. This could arise if parties that are in power invest more in regions in which they have a high share of the vote (to reward voters) or potentially increased investment in regions where vote share is lower (to encourage more votes in subsequent elections). These mechanisms could apply to national elections, as ZH investment is partly dependent on financial transfers to municipalities from federal government. They could also apply, however, in elections held at the municipality level as municipalities have substantial autonomy in deciding social policies and budget (29). We thus calculate three measures of electoral patterns using data from the Superior Electoral Court data repository (30): V1) Average municipal vote share (%), per municipality, in the presidential elections for the winning candidate, V2) Sum of years (over the focal period of our analysis) the municipality's mayor is from the same party as that of the current president, and V3) Sum of years the municipality's mayor is from a main party in Brazil. For V3 we create one variable for each of six major parties in Brazil (PMDB, PSDB, PFL, PTB, PP, and PT), as together they made up 70% and 67% of all mayor positions in the 2000-2010 and 2004-2013 periods, respectively. Elections are generally held in the fall therefore we only expect vote share for a winning party in one year, e.g. 2000, to have an influence on treatment allocation in the subsequent year, i.e. 2001. The contribution of each year to these three metrics is weighted by the proportion of investment that relates to that year, i.e. electoral patterns that could influence investment levels in years when investment in ZH is higher have greater weight. Relationships were consistently limited between investment and V2 (largest Spearmans' rho coefficient = 0.051) and V3 (largest Spearmans' rho coefficient = 0.149), but much larger correlations arose between investment and V1 (largest Spearmans' rho coefficient = 0.712: Table S9), and we thus select V1 as the most important variable to control for electoral patterns.

vii – ix) Land use. To account for any influence of the agricultural sector on our outcome variables we control for *Area under crop production-* (6) and *Area under pasture at baseline* (31). Area under crop production at baseline respectively refers to year 2000 and 2004 for the 2000-2010 and 2004-2013 models. Area under pasture is measured in 2006, a few years after our baselines as data for earlier years were not available. We use the 2006 census data rather than MapBioma' data because a large proportion of Brazil's farm area is classified as "agriculture or pasture" in the MapBiomass dataset (24% in version 3, accessed February 2019 www.mapbiomas.org/stats) thus creating considerable uncertainty in estimates of the amount of crop and pasture land.

We also control for the area of small-scale farms, i.e. *area by farms <50 ha at baseline* (31), again only available for 2006. We adopt this size threshold rather than the frequently used 2 hectare threshold because this excludes a substantial proportion of smallholder agriculture (32).

x) Remoteness. We control for remoteness, i.e. municipal travel time to a major city, which we use as a proxy for municipal access to larger markets and health services. We adapt the algorithm used by the Joint Research Centre of the European Commission (33), and incorporate information on land cover (34), transportation routes (35), and slope and elevation (36), to arrive at the fastest travel time from each municipality centroid to a major city, following Oldekop et al. (37). We use cities with at least 50,000 inhabitants as this is where large markets and adequate health services tend to be found (38, 39). Note that these travel times are correlated with travel times to both smaller and larger cities: 10,000 (r = 0.94), 150,000 (r = 0.86) and 250,000 inhabitants (0.74).

xi) Drought intensity. Drought could have adversely impacted our baseline and current food security measures (40–42). We calculate an average municipal drought index using the global Standardised Precipitation-Evapotranspiration Index (SPEI)(43). This continuous index ranges from -2 (extremely dry) to +2 (extremely wet) and is a standardized variable (mean zero and unit variance) expressed as the deviation of the current climatic balance (precipitation minus evapotranspiration potential) from the long-term (1901-2013) climatic balance. We use the average drought index per municipality, for three years spanning both sides of our baseline and endpoint years and then subtract the baseline index from the endpoint index to create a single measure which effectively captures the change in drought intensity over the period in which we measure the change in our outcome variables.

xii) Agricultural credit. We also consider possible effects of other farming assistance programs. We control for the amount of *rural agricultural credit* per capita (that is not PRONAF credit) regulated by the Brazilian Central Bank (44) allocated to each municipality for the full period in which we measure change in our outcome variables (2000-2010 and 2004-2013). We deflate these values relative to 2013, expressed per capita (in R$1,000 units) using population data from IBGE. Rural credit can influence food security (45, 46) and land use change (47).

xiii-xiv) Slope and elevation. We calculate and control for average slope (in degrees) and average elevation (in meters) per municipality using the global digital elevation model v2 (36), on the basis that both contribute to agro-ecological conditions which affect food production, natural vegetation cover and livelihoods (48).

xv) Conservation policies. We control for *Area under protection (at baseline)* when we model the effect of ZH investment on natural vegetation cover, based on previous studies showing the influence of protection on deforestation (20, 49). Boundaries of all designated protected areas, i.e. IUCN categories I-VI and indigenous areas, were obtained from the World database on Protected Areas (www.wdpa.org). We only consider protected areas established by 2004, but note that the area under protection by 2004 is highly correlated to the area under protection by 2013 (r = 0.97).

Methods

Covariate Balancing Generalized Propensity Score. We create Covariate Balancing Generalized Propensity Score weights (CBGPS) using the "CBPS" package (50) to capture potential treatment selection bias, i.e. dependence between treatment assignment and outcome given covariates (predictor variables), which if left untreated can bias the estimated effects of interest (51). The approach builds on previous methods of impact estimation using observational data, is shown to increase the robustness to model misspecification, and is applicable to a continuous treatment variable such as our measures of ZH investment (50).

The covariate balancing CBGPS method (50) offers both a parametric and non-parametric calculation to generate covariate balancing weights. In the parametric calculation a generalized propensity score is estimated by modelling treatment (i.e. level of ZH investment) as the function of pre-treatment covariates. Then inverse probability weights, whose aim is to ensure the lowest possible correlation between treatment and covariates, are created on the basis of the generalized propensity score. The non-parametric calculation does not directly estimate a generalized propensity score in the first instance but rather uses an empirical likelihood approach to choose inverse probability weights which ensure minimal correlation between treatment and covariates (for more detail see (50)).

We use both approaches and retain the weights that result in the greatest improvements in balance, i.e. the lowest correlation between investment (treatment) and confounding variables. We create distinct weights for each individual regression model, and use the same predictor variables to create the covariate balancing weights as those used in the subsequent adjusted regression model (see Table S1 for a full list of predictor variables used).

The weights resulted in great reductions in treatment-covariate correlations in all our regression models, and an average treatment-covariate correlation for each model of 0.07 (compared to an original average treatment-covariate correlation of 0.14) (Fig. S5).

Model structure and variable transformations. The appropriate model structure for each outcome variable was decided by fitting four potential theoretical distributions (normal, log-normal, Poisson and Negative binomial) to each outcome using R's "fitdistrplus" package (52). Daily per capita Kcalorie and protein production, multi-dimensional poverty (census), multi-dimensional poverty (SIAB) and natural vegetation cover fit a log-normal distribution and are subsequently modelled using ordinary least squares (OLS) regressions after transforming the dependent variables to log base ten. The investment variable and continuous covariates (except drought intensity and electoral patterns) are also transformed to log base ten, as this yields improved fit of linear relationships and Gaussian distributions of resultant model residuals. For the variables that include zero we add a constant of half of the minimum value before applying log transformations. Model diagnostics revealed the presence of outliers and we thus use R's "robustbase" package with the MM-estimator to conduct robust regressions that reduce the influence of outliers on model outputs (53). This frequently used technique has a high statistical efficiency and can cope with multiple outliers without breaking down (54). The MM-estimator also provides standard errors which are robust against heteroscedasticity and autocorrelation (54).

Child malnutrition (SIAB), infant mortality (census) and infant mortality (SIAB) were count data and exhibited over-dispersed Poisson distributions, tested using R's "AER" package (55). We modelled Infant mortality (SIAB) and Child malnutrition (SIAB) using a quasi-Poisson model and Infant mortality (census) using a negative binomial model. The choice between the two model structures was based on the outcome's mean-variance structure (56), selecting quasi-Poisson models when there was a linear relationship between the mean and variance. A robust MM-estimator cannot be calculated for Quasi-Poisson and Negative Binomial models. We thus follow the suggestion from Coxe et al. (57) and use another measure of influence, DFBETAS, to conduct analyses that are equivalent to robust regressions. DFBETAS can be calculated for each regression coefficient to "assess the number of standard deviations by which an individual changes each regression coefficient" p. 130 (57). Based on the most theoretically important variable for us – the investment variable – we run robust models which exclude highly influential points for the investment regression coefficient, defined as DFBETAS above the recommended DFBETAS cut-off of 2/sqrt (n) (57, 58).

Interaction terms. State and biome predictors are coded using deviation coding (also known as effect coding). State- investment and biome- investment interaction terms are retained when 95% confidence intervals (CIs) for the added parameter(s) exclude zero, and when there is improvement in model fit, judged for most models by a decrease in model's AIC value (of at least 2 AIC points) and judged in robust models calculated with an MM-estimator by adjusted R^2 values (59). State-investment interactions were retained when modelling per capita Kcalorie-, per capita protein and multi-dimensional poverty (census) as a function of summed ZH, PRONAF and BF investment, when using all data and when excluding lower quality data, as well as when modelling multi-dimensional poverty (SIAB) as a function of PRONAF investment using all data, and multi-dimensional poverty (SIAB) as a function of BF investment when excluding lower quality data. Biome-investment interactions were retained when modelling natural vegetation cover as a function of summed ZH, BF and PRONAF investment. All state and biome interaction effects are expressed relative to the main investment parameter which expresses the average effect across Brazil.

Visualising investment impacts. We use the resultant regression equations from core models to quantify the impact of investment by calculating the predicted value of our outcome variables under three scenarios i) a spatially uniform negligible investment level (defined as the 1st percentile investment value, thus ensuring we predict inside the range of our data), ii) the actual investment received in each municipality, and iii) spatially uniform investment levels equating to the 50th percentile investment level. We then generate maps of relative impact of actual investment (defined as percentage change in predicted outcome between a negligible and actual investment) (Fig. 1). Because ZH investment was highly spatially heterogeneous (Fig S1), we also generate maps of relative impact under a spatially uniform investment level (defined as percentage change in predicted outcome between a negligible and a 50th percentile investment level) (Fig. S2). This mapping approach helps to visualise spatial variation in the effectiveness of investment whilst accounting for heterogeneity in the magnitude of investment.

Robustness tests. We run robustness tests to look for potential sources of sampling bias or data quality issues, lack of independence amongst observations (spatial autocorrelation), and lack of independence between the treatment variable and error term (endogeneity). Checking for spatial autocorrelation and endogeneity also provide information on the potential presence of unmeasured confounders (60, 61).

Data Quality. We re-run models excluding municipalities for which there was uncertainty about data quality, defined as: i) municipalities larger than 10,000 km2 as larger municipalities are more likely to have unrepresentative socio-economic data (62); ii) for models using SIAB data (child malnutrition, infant mortality and multi-dimensional poverty) municipalities that did not meet the ten quality criteria set by Brazil's Ministry of Health for SIAB data (63) (e.g. municipalities with small sample sizes in the microdata (e.g. <100 families/350 people registered with data), limited temporal data (e.g. municipalities with 0 families attended to in a month), or non-logical data (e.g. >1000 infant deaths per 1000 live births) (see Table S10 for a full list of criteria), and iii) for natural vegetation cover models, municipalities in which cloud cover in the natural vegetation dataset covered more than 5% of the surface area in either 2004 (the baseline) or 2013 as this could reduce the accuracy of natural vegetation cover estimates.

The number of municipalities excluded due to possible quality issues range from 98 to 1,847 depending on the outcome variable (Table S10). Exclusions based on municipality size, employed to all models, exclude 0-61% of municipalities in a state with the largest effects in northern and centre-western states. Exclusions based on high cloud cover, employed to the natural vegetation cover models, affect 12 of 16 states situated in the north or north-east, and one state elsewhere (Rio Grande do Sul in the south) reducing state sample sizes by between 1 and 75%. The largest exclusions occur in models using SIAB data (multi-dimensional poverty-, child malnutrition-, and infant mortality) based on the Ministry of Health's quality criteria, with 15 to 100% of municipalities being excluded per state. Whilst

Amapa (in the north) was the only state from which all municipalities were excluded there is no marked geographical variation in the percentage of municipalities that are excluded. When combining data quality criteria robustness models excluded 77.0% and 99.7% of the Amazon and Pantanal biomes' area, thus generating significant spatial bias. We thus exclude these biomes from the robustness models assessing change in natural vegetation cover.

In a quarter of the models (6 of 24) inference varies between core and robustness models (i.e. the PRONAF and per capita Kcalorie production and natural vegetation change models, BF and SIAB derived multi-dimensional poverty model, the BF infant mortality (SIAB) model, and when assessing the impact of overall ZH and BF investment on natural vegetation change in the Caatinga) we discuss discrepancies in the main text (although the impact on our inference is rather limited). In all other cases inference from the robustness and core models was extremely similar and we focus on the results from the core model as this enables us to visualise modelled impacts across Brazil. There were occasional small differences, however, in the precise location and extent of areas in which treatment impacts are significant and non-negligible. Specifically, i) in one state (Para in the north) the effect of PRONAF investment on per capita protein production changes from a predicted increase in outcome in the core model to a predicted reduction in the robustness model; and ii) in one state (Mato Grosso in the central west) the effect of BF investment on per capita protein production changes from a predicted reduction in outcome in the core model to a predicted increase in the robustness model).

Spatial autocorrelation. We assess the presence of spatial autocorrelation, given that this can violate the assumption of independence in classical statistics and influence results (64). Spatial autocorrelation also indicates that spatially determined unmeasured confounders may be present, further facilitating assessment of endogeneity (61). We test for spatial autocorrelation using two-sided Moran's I tests implemented in R's "spdep" package (65) on all core model residuals and model residuals from the covariate balancing stage (CBGPS). As only the parametric, and not the non-parametric, CBGPS models can provide residuals (50) we follow Oldekop et al. (66) and create our own propensity score models, i.e. in our case linear regressions where investment is the function of predictor variables, and test for spatial autocorrelation in the residuals of these models. We do so using first a simple spatial neighbourhood matrix that classifies municipalities as neighbours if they share a common border. We then use a distance based neighbourhood matrix that generates a weight matrix based on inverted euclidian distance between each municipality centre, though capped at 0.75 of the maximum given the extreme sizes of some Brazilian municipalities.

Moran's I values for 78% of our models were not statistically significant. Where Moran's I values were significant they were very close to zero (range -0.027 to 0.031; Table S11). We thus conclude that our model inference is not biased by spatial autocorrelation and that there is no evidence that spatially determined unmeasured confounders influence our outcomes variables.

Endogeneity. Endogeneity between model error terms and investment variables can influence causal inference and such endogeneity is typically caused by unmeasured confounding variables (60). A Hausman test can be used to test for endogeneity. This requires identifying the omitted variable that generates endogeneity, but this is rarely possible in observation studies (as is the case for our models), and selection of appropriate instrumental variables – which is often difficult (60). In the absence of the Hausman test we follow Oldekop et al.(66), and assess whether the error term (model residuals) and investment variable are correlated running a series of non-parametric Spearman's rho correlation tests. The correlation coefficients (Spearman's rho) between model residuals and the model investment variable are very low for all core models and range from -0.085 to 0.049 (Table S12). Thus, we conclude there is no evidence of endogeneity between our investment variables and model error term, providing further evidence that it is unlikely that unmeasured confounders influence or bias our results.

Supplementary Tables

Table S1. Model variables for the Zero Hunger (ZH)-, Bolsa Familia (BF)- and PRONAF models

Outcome	Treatment	Confounding variables																							n
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	
$\log_{10}$(Kcal (pc))	$\log_{10}$(ZH)* State $\log_{10}$(BF)* State $\log_{10}$(PRONAF)* State	✓	✓	✓		B		✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,940
$\log_{10}$(Protein (pc))	$\log_{10}$(ZH)* State $\log_{10}$(BF)* State $\log_{10}$(PRONAF)* State	✓	✓	✓			B	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,940
$\log_{10}$(Multi-dim. poverty (census))	$\log_{10}$(ZH)* State $\log_{10}$(BF)* State $\log_{10}$(PRONAF)* State	✓	✓	✓		✓		B				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,976
$\log_{10}$(Multi-dim. poverty (SIAB))	$\log_{10}$(ZH) $\log_{10}$(BF)* State $\log_{10}$(PRONAF)* State	✓	✓	✓		✓		B				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		3,786
Child malnutrition (SIAB)	$\log_{10}$(ZH) $\log_{10}$(BF)* State $\log_{10}$(PRONAF)	✓	✓	✓		✓		✓		B		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		3,828
Infant mortality (census)	$\log_{10}$(ZH) $\log_{10}$(BF) $\log_{10}$(PRONAF)	✓	✓	✓		✓		✓	B			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,976
Infant mortality (SIAB)	$\log_{10}$(ZH) $\log_{10}$(BF) $\log_{10}$(PRONAF)	✓	✓	✓		✓		✓	B			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,305
$\log_{10}$(Natural vegetation (km2))	$\log_{10}$(ZH)*Biome (6cat) $\log_{10}$(BF)*Biome (6cat) $\log_{10}$(PRONAF)*Biome (6cat)	✓	✓		✓			✓			B	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4,924

Pc = per capita. B = baseline conditions of the outcome variable. N = model sample size. Outcome years correspond to 2010 for multi-dimensional poverty (census) and Infant mortality (census) (with corresponding baseline (B) values from 2000), all other outcomes for year 2013 (with B values from 2004). Three treatments are tested separately, i.e. total municipal ZH (sum of BF, PRONAF, PAA and PNAE), BF and PRONAF investment per capita from baseline to endpoint year. The confounding variables, whose inclusion in each model are indicated by ticks/B, are 1. ZH investment that is not captured in the sub-program (included in the BF and PRONAF models only), 2. State, 3. Biome (13cat), 4. Biome (6cat), 5. Kcal (pc), 6. Protein (pc), 7. Multi-dimensional poverty (census or SIAB), 8. Infant mortality (census or SIAB), 9. Child malnutrition (SIAB), 10. Natural vegetation (km2), 11. GDP Public administration (pc), 12. Crop area (ha), 13. Pasture area (ha), 14. Small-scale farm area (ha), 15. Drought intensity, 16. Rural credit (pc), 17. Remoteness (Minutes), 18. Elevation (meter), 19. Slope (degree), 20. Municipal area (km2), 21. Population density, 22. Electoral patterns, and 23. Protected area (km2). Some models include an interaction term between treatment and state or biome (indicated by *). For the natural vegetation models Biome (6cat) is used instead of Biome (13cat), because the latter variable had too small sample sizes across the seven transition-biome categories for the models to run successfully with biome interaction effects. Time-variant confounding variables which might risk being influenced by the treatment are set at the baseline year to minimize influence from investment. Some exceptions exist, i.e. data for 13. Pasture area, and 14. Small-scale farm area are only available for 2006. Also, 7. baseline multi-dimensional poverty (census), which corresponds to year 2000, is used as a baseline confounding variable for the 2004-2013 Kilocalorie-, Protein- and Natural vegetation models as opposed to multi-dimensional poverty (SIAB) (which corresponds to year 2004) because the geographical coverage of multi-dimensional poverty (census) better matches the coverage of these outcome variables). Confounding variable 16. Rural credit incorporates data for the whole time-period as it is likely unaffected by treatment. Likewise 15. Drought intensity, incorporates three years spanning our baseline and endpoint years. All continuous variables besides the outcome for Infant mortality and Child malnutrition, and the Drought intensity confounding variable are transformed to log base 10.

Table S2. Descriptive statistics for all Zero Hunger (ZH)-, Bolsa Familia (BF)- and PRONAF model variables.

Variable	Description	Time frame	Mean	SD
Dependent variables (and corresponding baseline values):				
Kcal (pc/day)	Kilocalories produced per capita per day (pc/day) in 2013 and 2004	Endpoint Baseline	157,902 84,420	442,278 240,796
Protein (gram pc/day)	Grams of protein produced per capita per day in 2013 and 2004	Endpoint Baseline	1,975 1,410	5,665 3,916
Multi-dim. poverty (census)	Multi-dimensional poverty index for the entire population in 2010 and 2000	Endpoint Baseline	0.058 0.116	0.031 0.06
Multi-dim. poverty (SIAB)	Multi-dimensional poverty index in the poorer sectors of society in 2013 and 2004	Endpoint Baseline	0.059 0.07	0.039 0.04
Underweight children (SIAB)	Geometric mean of number of underweight children at birth- and age 12-24 months per 10,000 children in the poorer sectors of society 2013 and 2004	Endpoint Baseline	253 665	290 458
Infant mortality (census)	Number of infant (<1 year) deaths per 100,000 live births for the entire population in 2010 and 2000	Endpoint Baseline	1,958 3,393	717 1,388
Infant mortality (SIAB)	Number of infant (<1 year) deaths per 100,000 live births in the poorer sectors of society in 2013 and 2004	Endpoint Baseline	2,255 2,547	11,072 2,589
Natural vegetation cover (km^2)	Total area (km^2) under natural vegetation in 2013 and 2004	Endpoint Baseline	1,078 1,103	5,331 5,402
Treatment variables:				
ZH (R$/pc)	Total per capita ZH investment in Brazilian Reals, i.e. sum of per capita BF, PRONAF, PAA and PNAE for 2000-2010; and 2004-2013	Total	2,550; 3,829	2,704; 3,948
BF (R$/pc)	Total BF investment per capita for 2004-2010; and 2004-2013	Total	692; 1,216	398; 696
PRONAF (R$/pc)	Total PRONAF investment per capita for 2000-2010; and 2004-2013	Total	1,716; 2,439	2,796; 4,118
Confounding variables:				
Multi-dim. poverty (census)	Census based multi-dimensional poverty index for year 2000	Baseline	0.116	0.06
GDP Public Service (R$/pc)	GDP from public services per capita for years 2000; and 2004	Baseline	1,533; 1763	535; 554
Kcal (pc/day)	Kilocalories produced per capita per day for years 2000; and 2004	Baseline	66,397; 84,420	201,853; 240,796
Crop area (ha)	Total crop area for years 2000; and 2004	Baseline	9,643; 11,322	21,258; 26,845
Election pattern (% vote share)	Average municipal vote share for the winning presidential candidate (%) for 2000-2010; and 2004-2013, with contribution of each years' vote share weighted by the proportion of investment for that year	2000-2010 ZH BF PRONAF 2004-2013 ZH BF PRONAF	 59 59 59 60 60 60	 11 13 10 13 13 14
Pasture area (ha)	Total pasture area for year 2006	Baseline	31,003	81,712
Small-scale farm area (< 50 ha)	Total hectare farms <50 hectare for year 2006	Baseline	8,379	8,627
Remoteness (min.)	Travel time in minutes from the municipality centroid to the nearest city with pop => 50,000 in 2010		187	410
Drought intensity	Drought intensity, based on SPEI for baseline and endpoint periods (see SI Appendix for detailed description)	Total	1.4; 0.37	2; 2.24
Credit (R$/pc)	Total rural non-PRONAF agricultural credit for 2000 – 2010; and 2004 – 2013	Total	7,280; 9,427	12,708; 16,306
Elevation (m)	Average elevation within each municipality		456	281;
Slope (degree)	Average slope within each municipality		8.2	3.8;
Pop.Density	Total population per km^2 for years 2000; and 2004	Baseline	30; 31	29; 30
Municipality area (km^2)	Area within municipality boundaries in 2000; area within municipality boundaries in 2004; and area that was cloud free in both 2004 and 2013 within 2004 municipality boundaries	Baseline	1,630; 1,619; 1,573	5,939; 5,902; 5,712
Protected area (km^2)	Total area classified as strictly protected-, sustainable use protected areas and indigenous. area at baseline year 2004	Baseline	300	2407
State	26 levels (Federal District excluded because urban)			
Biome	13 levels (6 pure biome and 7 transition zones)			

Dependent variables and their baseline variable values are based on model sample sizes ranging 3,808-4,976 municipalities. Treatment and confounding variable values are based on the largest 2000-2010 and 2004-2013 model sample (n = 4,976 and

4,940, respectively). Confounding variables with single values are based on the largest model sample in which the variable is used.

Table S3. Quality dataset robustness check model impacts of Zero Hunger (ZH), Bolsa Familia (BF) and PRONAF per capita investment

	ZH				BF				PRONAF			
Outcome	**Coef±S.E.**	**P**	**Int.**	**R^2**	**Coef±S.E.**	**P**	**Int.**	**R^2**	**Coef±S.E.**	**P**	**Int.**	**R^2**
Kcalories (per capita)	0.01±0.02	0.629	2E-08	0.94	0.02±0.02	0.212	1E-20	0.93	0.02±0.01	0.148	7E-12	0.94
Protein (per capita)	0.08±0.02	3.E-07	2E-42	0.96	0.09±0.02	3.E-05	1E-17	0.96	0.04±0.01	0.002	9E-103	0.96
Multi-dim. poverty (census)	-0.01±0.01	0.022	2.E-04	0.74	0.04±0.01	8.E-07	3E-08	0.77	-0.02±0.005	4.E-05	3E-10	0.76
Multi-dim. poverty (SIAB)	0.02±0.01	0.116		0.61	0.03±0.03	0.202	5.E-04	0.61	-0.02±0.02	0.230		0.60
Child Malnutrition (SIAB)	0.04±0.04	0.334		n/a	0.15±0.07	0.025		n/a	-0.01±0.03	0.683		n/a
Infant Mortality (census)	0.01±0.24	0.983		0.13	0.03±0.27	0.898		0.14	0.01±0.22	0.962		0.17
Infant Mortality (SIAB)	0.07±0.06	0.241		n/a	0.11±0.07	0.147		n/a	-0.04±0.05	0.439		n/a
Natural Veg. (km2)	-0.01±0.004	0.005	9.E-05	0.99	-0.03±0.01	0.007	0.040	0.99	-0.01±0.004	0.169	3.E-05	0.99

Model coefficients are reported ± one standard error. Interaction terms (Int.) show p-values for the interactions between investment and state in all models, except for the natural vegetation model in which the interaction is with biome type. When interaction terms are not significant we report results from models that only contain main effects. State and biome have been encoded with deviation (effects) coding, thus for models with an interaction the main effects expressed here represent the average effect of investment across Brazil. Daily per capita kilocalorie and protein production, multi-dimensional poverty and area of natural vegetation are modelled using robust OLS, whilst infant mortality (census) is modelled using a Negative Binomial model, and infant mortality- and child malnutrition (SIAB) are modelled with a Quasi-Poisson model. Model r^2 for infant mortality (census) is calculated using McFaddens pseudo-R^2 and is thus not comparable to those from OLS models. No pseudo-r^2 is available for Quasi-Poisson models. All models have been adjusted to achieve covariate balance using the CBGPS method (50).

Table S4. Robustness check model of the impact of Bolsa Familia (BF) per capita (pc) investment on education

	BF			
Outcome	**Coef±S.E.**	**P**	**Interaction term**	**R^2**
Education (census)	0.08±0.07	0.263	2.E-10	0.34
Education (SIAB)	-1.11±1.12	0.320	2.E-08	0.11

Due to a heavy negative skew in the Education (census) dependent variable, an Ordered Quantile (ORQ) normalization transformation was carried out. This transformation was identified as the best transformation (out of 7 standard transformations) using R's package "bestNormalize". Model coefficients are reported ± one standard error. Interaction terms report p-value for the interaction term between investment and state. In the Education (census) model 7 states showed a significant effect of BF investment on school attendance (Para, Rondonia, Alagoas and Bahia with significant increases, and Goias, Mato Grosso do Sul, and Parana with significant reductions). In the Education (SIAB) model 4 states showed a significant effect of BF investment on school attendance (Parana and Santa Catarina with significant increases, and Bahia and Piaui with significant reductions) State has been encoded with deviation (effects) coding, thus for models with an interaction the main effects expressed here represent the average effect of investment across Brazil. Both education models are modelled using covariate balance (CBGPS) adjusted robust OLS models.

Table S5. Nutrient values used to convert production of (a) kg and (b) number of animals to corresponding quantities in kilocalories and grams of protein

Agro-Livestock	products	Kcal FBA/USP estimate	Kcal USDA estimate	**Kcal value used**	Protein FBA/USP estimate	Protein USDA estimate	**Protein value used**
(a)							
Sugarcane		-	3,750	**3,750**	-	0	**0.00**
Soyabeans		3,630	4,460	**4,045**	405	360	**382.50**
Maize		-	3,650	**3,650**	-	90	**90.00**
Rice		3,400	3,650	**3,525**	78.1	70	**74.05**
Cassava		1,330	1,600	**1,465**	13	10	**11.50**
Milk		650	600	**625**	29.7	30	**29.85**
(b)	**Kg meat/ animal**						
Cattle	134.5[a]	1,388	2,340	**1,864**	200.7	190	**195.35**
Buffalo	218.5[b]	-	1,090	**1,090**	-	210	**210.00**
Chicken	1.7[c]	2,090	-	**2,090**	171	-	**171.00**
Sheep	6.5[d]	1,090	-	**1,090**	207.4	-	**207.40**
Goat	5.8[e]	-	1,090	**1,090**	-	210	**210.00**
Pig	45.4[f]	1,720	1,850	**1,788**	198.7	195	**196.85**

Twelve main agro-livestock products in Brazil are converted from (a) kg and (b) number of animals to corresponding quantities in kilocalories and grams of protein. For (b) each livestock type is first assigned an average weight of meat, and based on appropriate quantities in a Brazilian context converted from number of animals to kg, sources used being a(67), b(68), c(69), d(70), e(71), and f(72). Nutrient values are taken from the Brasilfoods (7) and USDA database (8), the average of the two used when possible, expressed here as kilocalories and grams of protein per kg

Table S6. Data included to create the multi-dimensional poverty indices Multi-dimensional poverty (census) and Multi-dimensional poverty (SIAB).

	Multi-dimensional poverty (census)		**Multi-dimensional poverty(SIAB)**	
Health	Infant mortality (infant deaths per 1,000 births)		Infant mortality (infant deaths per 1,000 births)	
	Life expectancy deprivation (deviation from expected living age w/global min and max years): 1-((LifeExpectancy-20)/(85-20))		Child malnutrition (underweight per 100 weighted)	Underweight at birth (per 100 weighed)
				Underweight age 1-2 (per 100 weighed)
Education	No school attendance (% 7-14 year olds that do not attend primary school)		No school attendance (% 7-14 year olds that do not attend primary school)	
Living standards	No electricity (% people without access to electricity)		No electricity (% people* without access to electricity)	
	Unsafe water (% people without piped water)		Unsafe water (% people* without piped water)	
	Inadequate sanitation (% people* without public system or septic tank)		Inadequate sanitation (% people* without public system or tank)	
	No assets (% people without access to:)	TV	Inadequate walls (% people*living in houses with inadequate walls such as cardboard, plastic and straw)	
		Radio		
		Telephone		
		Car		
		Fridge/freezer		
		Washing machine		

Data included to create multi-dimensional poverty (census) is based on the Brazilian demographic census (73) while multi-dimensional poverty (SIAB) on the national primary information system (SIAB) (12). All variables besides *Life expectancy deprivation* is expressed as the proportion of people. *indicates an original measure of %-households has been converted to %-people based on average people per household per municipality published by IBGE. Each variable is negatively loaded and scaled between 0-1, and subsequently combined through geometric means to make higher order compound variables, the final indices ranging 0-1 where 1 equals complete multi-dimensional poverty

Table S7. Vegetation cover categories from MapBiomas used to create an overall natural vegetation classification

MapBiomas categories	**New categories**
Forest, Natural forest formations, Dense forest, Open forest, Mangrove forest, Flooded forest, Degraded forest, Secondary forest, Natural non-forest formations, Non-forest natural wetlands, Grasslands*, and Other non-forest natural formations	Natural vegetation
Planted forest, Agro-livestock use, Pasture, Pasture in natural grasslands, Other pasture, Agriculture, Annual crops, Semi-perennial crops (Sugarcane), Crop mosaics, Agriculture or pasture, Non-vegetative areas, Beaches and dunes, Urban infrastructure, Other non-vegetative areas, and Water bodies	Other
Non observed	Non observed

Vegetation cover categories are taken from MapBiomas v2(16), and the overall natural vegetation classification created used to analyse the impact of Zero Hunger, Bolsa Familia and PRONAF investment on municipal area under natural vegetation. *Natural grasslands, i.e. not including pasture

Table S8. Robustness check validating the accuracy of natural vegetation cover estimates per biome from MapBiomas (MB), using alternative data sources.

Biome	Alternative land use	Resolution	Year	% cover of natural vegetation from Map Biomass	% cover of natural vegetation from alternative data source	Spearman's rho correlation coefficients comparing Map Biomass and alternative data sources' estimates of natural vegetation cover per municipality	N
Amazon	Terra Class	30 m	2014	83	86	0.992	399
Cerrado	Terra Class	1:250,000	2013	56	55	0.977	809
Cerrado	PMDBBS	1:250,000	2002	58	57	0.969	833
Caatinga	PMDBBS	1:250,000	2002	64	54	0.899	898
Atlantic Forest	SOS Mata Atlantica	1:250,000	2013	28	14	0.865	2448

The accuracy of the 30 m resolution fine-scale natural vegetation maps of MapBiomas v2(16) is validated by considering the extent of natural vegetation categorized by MapBiomas (MB) compared to alternative vegetation maps within four main Brazilian biomes (Amazon, Cerrado, Caatinga and Atlantic Forest). TerraClass has a minimum detected area of approximately 6.25 ha (74). First, we compare estimates of natural vegetation cover (%) as a proportion of total biome area using data from all municipalities. The discrepancy in natural vegetation cover for the Atlantic Forest is most likely caused by the lower resolution of the alternative map (SOS Mata Atlantica) and subsequent inability to pick up on the many small and fragmented natural vegetation areas typical for this biome. Second, Spearman's rho correlations are calculated for the two estimates of natural vegetation cover (km^2) per municipality, N refers to the number of municipalities included in these analyses. Pre-processed Terra Class data for the Amazon were not available so we only use municipalities for which both data sources had extremely similar estimates of municipality size (<1% difference).

Table S9. Correlation coefficients and associated P values for relationships between ZH-, BF and PRONAF investment and electoral patterns in Brazil

		ZH		BF		PRONAF	
Time frame	Party	Spearman's rho	P	Spearman's rho	P	Spearman's rho	P
V1: Average municipal vote share (%) in presidential elections for the winning candidate							
2000-2010		**-0.076**	**8E-08**	**0.648**	**0E+00**	**-0.342**	**2E-136**
2004-2013		**0.064**	**6E-06**	**0.712**	**0E+00**	**-0.285**	**7E-93**
V2: Sum of years the municipality is governed by the same party as the current president							
2000-2010		-0.051	0.0003	-0.046	0.001	-0.026	0.068
2004-2013		-0.004	0.775	-0.041	0.004	0.003	0.861
V3: Sum of years the municipality is governed by a main party in Brazil							
2000-2010	PMDB	0.097	9E-12	-0.113	2E-15	0.122	8E-18
2004-2013	PMDB	0.091	2E-10	-0.111	6E-15	0.117	2E-16
2000-2010	PSDB	-0.147	2E-25	-0.059	3E-05	-0.089	4E-10
2004-2013	PSDB	-0.154	2E-27	-0.088	7E-10	-0.077	8E-08
2000-2010	PFL	-0.001	0.953	0.149	4E-26	-0.057	0.0001
2004-2013	PFL	0.009	0.517	0.150	4E-26	-0.057	0.0001
2000-2010	PTB	-0.028	0.053	0.057	0.0001	-0.038	0.007
2004-2013	PTB	-0.021	0.144	0.056	0.0001	-0.034	0.017
2000-2010	PP	0.120	3E-17	-0.101	1E-12	0.121	1E-17
2004-2013	PP	0.117	2E-16	-0.109	2E-14	0.145	1E-24
2000-2010	PT	-0.009	0.528	-0.046	0.001	0.017	0.219
2004-2013	PT	-0.004	0.775	-0.041	0.004	0.003	0.861

Data on electoral patterns from the presidential elections (V1) and municipal elections (V2 and V3) for the time frames of the analysis (2000-2010 and 2004-2013) are taken from the Superior Electoral Court data repository (30).The contribution of each year to these three metrics is weighted by the proportion of investment that relates to that year, i.e. electoral trends in years when investment in ZH is higher have greater weight. Spearman's Rho correlations between the electoral variables and ZH-, BF- and PRONAF investment variables show clear signs of a relationship with V1 (highlighted in bold), but no relationship with V2 and V3, thus V1 is selected as a control variable.

Table S10. Criteria, thresholds and rational used to exclude municipalities (M) from specific models to reduce bias in model estimates.

		Criteria	Threshold	Rational for exclusion	Models affected	M excluded
Core models	1.1	Inconsistent municipality borders	Merging municipalities for time periods 2004-2013 and 2000-2010	Spatial inconsistency	All	4 – 45
	1.2	Inconsistent municipality borders	Border change 2000–2004	Spatial inconsistency	Kilocalorie, Protein and Natural vegetation	128
	2	Urban municipalities	> 150 inhabitants/km²	Not target municipalities	All	407 – 438
	3	Unidentifiable municipality IDs	Mis-spelled names	Erroneous reporting	All	3 – 20
	4	Non-observed municipal area due to cloud cover	> 50%	Spatial inconsistency	Natural vegetation	17
	5	Missing information	Missing predictor variable information	Predictor variable inconsistency	All	55 – 1307
Robustness models	6	Municipality size (km^2)	> 10000	Sampling bias	All	98 – 130
	7	Families registered	< 100	Bias due to small sample size	Child malnutrition (SIAB), Infant mortality (SIAB) , Multi-dimensional poverty (SIAB)	566 – 1847
		People registered	< 350	Bias due to small sample size		
		People registered within in all age groups	0	Bias due to small sample size		
		Families attended to each month	0	Temporal bias		
		Monthly medical visits to people with pregnancy, hypertension, diabetes, tuberculosis and leprosy	< 10%	Temporal bias		
		Deviation between sum of people of all ages and total people registered	> 10%	Erroneous reporting		
		Infant mortality rate (deaths per 1,000 born)	> 1,000	Erroneous reporting		
		Average people per family	< 2 or > 8	Erroneous reporting		
		Sex ratio	< 0.5 or > 2	Erroneous reporting		
		Average monthly visits per family	< 0.2 or > 4	Erroneous reporting		
	8	Non-observed municipal area due to cloud cover	> 5%	Spatial inconsistency	Natural vegetation	323

Number of municipalities excluded per criteria vary across model sample sizes because they rely on data for different time periods, i.e. 2000-2010 and 2004-2013, and have slight variations in model covariates. The reported number of municipalities excluded are based on a sequential exclusion. According to criteria 1.1, municipalities which merged to form single municipalities within a time period were excluded. The additional exclusions in criteria 1.2 for the kilocalorie, protein and natural vegetation models occur because these models include a control variable adjusted to municipality borders for year 2000 (the census derived multi-dimensional poverty index), while all other data is adjusted to 2004 municipality borders. Thus all municipalities with border discrepancies between 2000 and 2004 had to be excluded. Criteria seven is based on formal suggestions for SIAB data (63).

Table S11. Two-sided Moran's I test on ZH-, BF- and PRONAF model residuals show no signs of spatial autocorrelation.

	Zero Hunger				**BF**				**PRONAF**			
	Border		Distance		Border		Distance		Border		Distance	
Model	Moran's I	P	Moran's I	P	Moran's I	P	Moran's I	P	Moran's I	P	Moran's I	P
CBGPS residuals												
Kcalories (per capita)	-0.0177	0.051	-0.0057	0.069	-0.0002	0.997	0.0028	0.316	-0.0097	0.289	-0.0078	**0.012**
Protein (per capita)	-0.0160	0.078	-0.0039	0.221	-0.0002	0.999	0.0033	0.251	-0.0065	0.481	-0.0056	0.076
Multi-dim. povertyCensus	-0.0134	0.135	-0.0023	0.496	-0.0223	**0.013**	-0.0031	0.340	-0.0088	0.331	-0.0016	0.639
Multi-dim. povertySIAB	0.0313	**0.006**	0.0007	0.718	0.0063	0.571	-0.0007	0.861	0.0112	0.323	-0.0021	0.473
Child MalnutritionSIAB	-0.0095	0.439	-0.0048	0.095	-0.0107	0.377	-0.0035	0.236	0.0073	0.523	-0.0061	**0.032**
Infant MortalityCensus	0.0006	0.928	-0.0022	0.520	-0.0188	**0.047**	-0.0083	**0.008**	-0.0168	0.074	-0.0047	0.158
Infant MortalitySIAB	-0.0167	0.122	-0.0108	**0.001**	-0.0272	**0.011**	-0.0103	**0.001**	0.0037	0.710	-0.0065	**0.042**
Natural Veg. (km2)	0.0151	0.088	-0.0005	0.911	-0.0036	0.708	0.0042	0.146	-0.0053	0.570	-0.0049	0.125
Outcome residuals												
Kcalories (per capita)	0.0210	**0.018**	0.0070	**0.018**	0.0180	**0.042**	0.0064	**0.029**	0.0194	**0.029**	0.0067	**0.024**
Protein (per capita)	-0.0038	0.691	-0.0020	0.553	-0.0069	0.455	-0.0035	0.284	-0.0047	0.615	-0.0002	0.998
Multi-dim. povertyCensus	-0.0129	0.153	-0.0016	0.648	-0.0108	0.232	-0.0006	0.887	-0.0079	0.383	-0.0007	0.856
Multi-dim. povertySIAB	0.0009	0.920	-0.0009	0.803	0.0015	0.880	0.0005	0.784	0.0004	0.953	-0.0017	0.579
Child MalnutritionSIAB	-0.0070	0.573	-0.0009	0.831	-0.0070	0.538	0.0061	**0.010**	-0.0034	0.795	-0.0006	0.906
Infant MortalityCensus	-0.0110	0.241	-0.0038	0.250	-0.0005	0.979	-0.0061	0.052	0.0149	0.104	0.0010	0.699
Infant MortalitySIAB	-0.0148	0.172	-0.0036	0.264	-0.0006	0.971	0.0008	0.729	0.0224	**0.029**	0.0015	0.557
Natural Veg. (km2)	0.0071	0.415	0.0092	**0.002**	0.0057	0.513	0.0073	**0.013**	0.0054	0.534	0.0071	**0.016**

Two-sides Moran's I tests were run on model residuals from the covariate balancing models where CBGPS weights were created (CBGPS residuals) and on residuals from the subsequent CBGPS weighted regression models (Outcome residuals). The Moran's I tests were run twice and based on distinct spatial neighbourhood matrices, i) a neighbourhood matrix based on touching municipality borders (labelled Border in the table), and ii) a neighbourhood matrix defined as the inverse distance between each municipality centroid, which was capped at 0.75 of the maximum distance (labelled Distance in the table). No signs of spatial autocorrelation were found, as even significant Moran's I values ($P < 0.05$, highlighted in bold) have Moran's I values very close to 0

Table S12. A semi-formal test for endogeneity(66) show no signs of endogeneity between the error term and ZH-, BF and PRONAF investment variables

	ZH	**BF**	**PRONAF**
Model	Spearman's rho	Spearman's rho	Spearman's rho
Kcalories (per capita)	0.005	-0.024	0.008
Protein (per capita)	0.009	-0.013	0.010
Multi-dim. poverty (census)	-0.003	0.003	-0.001
Multi-dim. poverty (SIAB)	0.002	0.001	0.002
Child Malnutrition (SIAB)	-0.014	-0.070	-0.066
Infant Mortality (census)	-0.012	-0.080	0.049
Infant Mortality (SIAB)	-0.049	-0.032	-0.085
Natural Veg. (km2)	-0.006	-0.032	-0.006

The semi-formal test for endogeneity is based on Spearman's Rho correlations between the error term (model residuals) and the ZH-, BF- and PRONAF investment variables. All Spearman's rho values are very low and show no signs of endogeneity

Supplementary Graphs

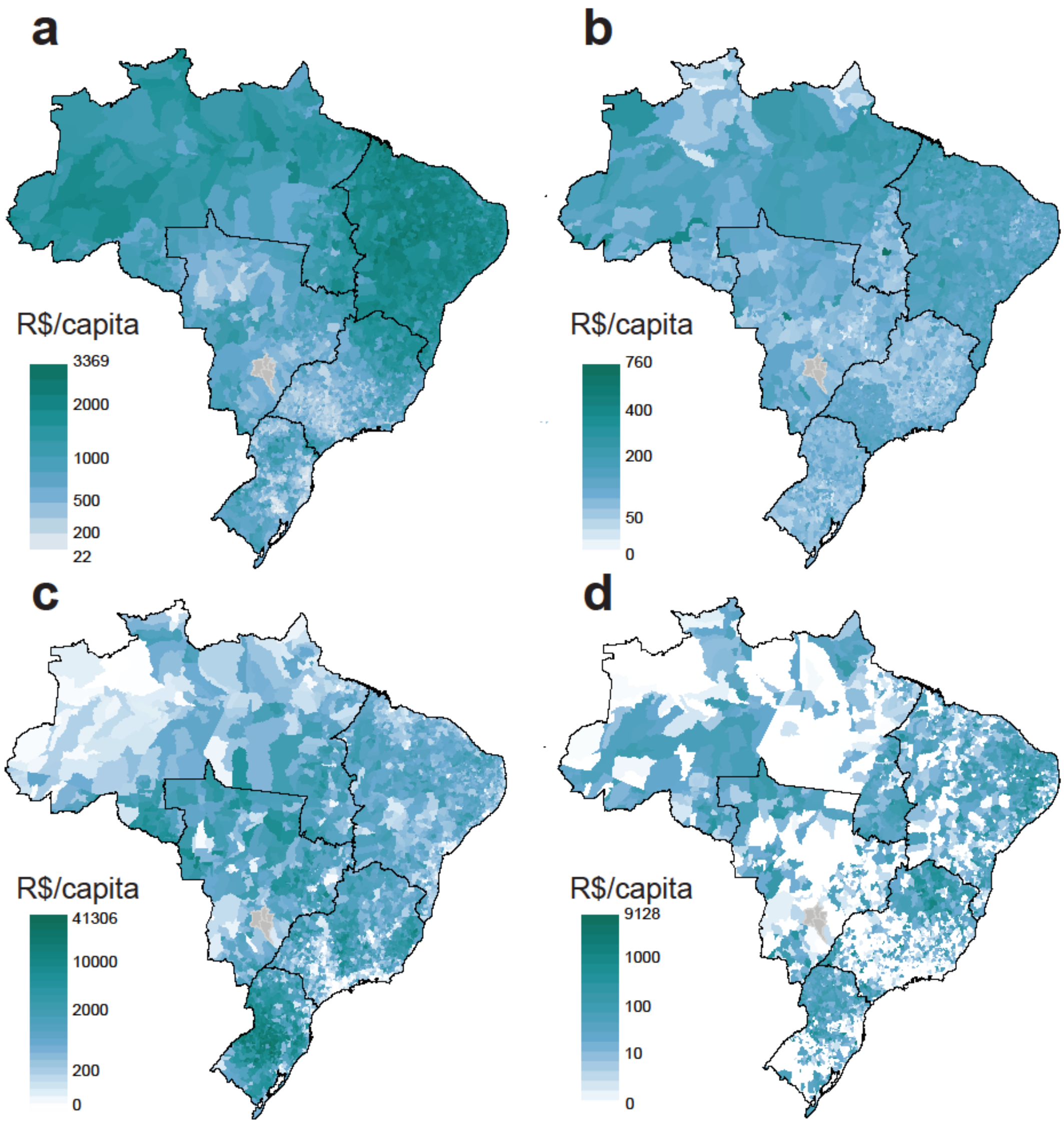

Fig. S1. Total investment per capita in Brazilian reals (R$) from 2004-2013 for the main Zero Hunger sub-programs **a** Bolsa Familia, **b** PNAE, **c** PRONAF and **d** PAA, available at www.dados.gov.br/www.mds.gov.br, showing great spatial variation in investment within and across programs. Grey areas indicate municipalities not included. Dark borders show administrative region borders

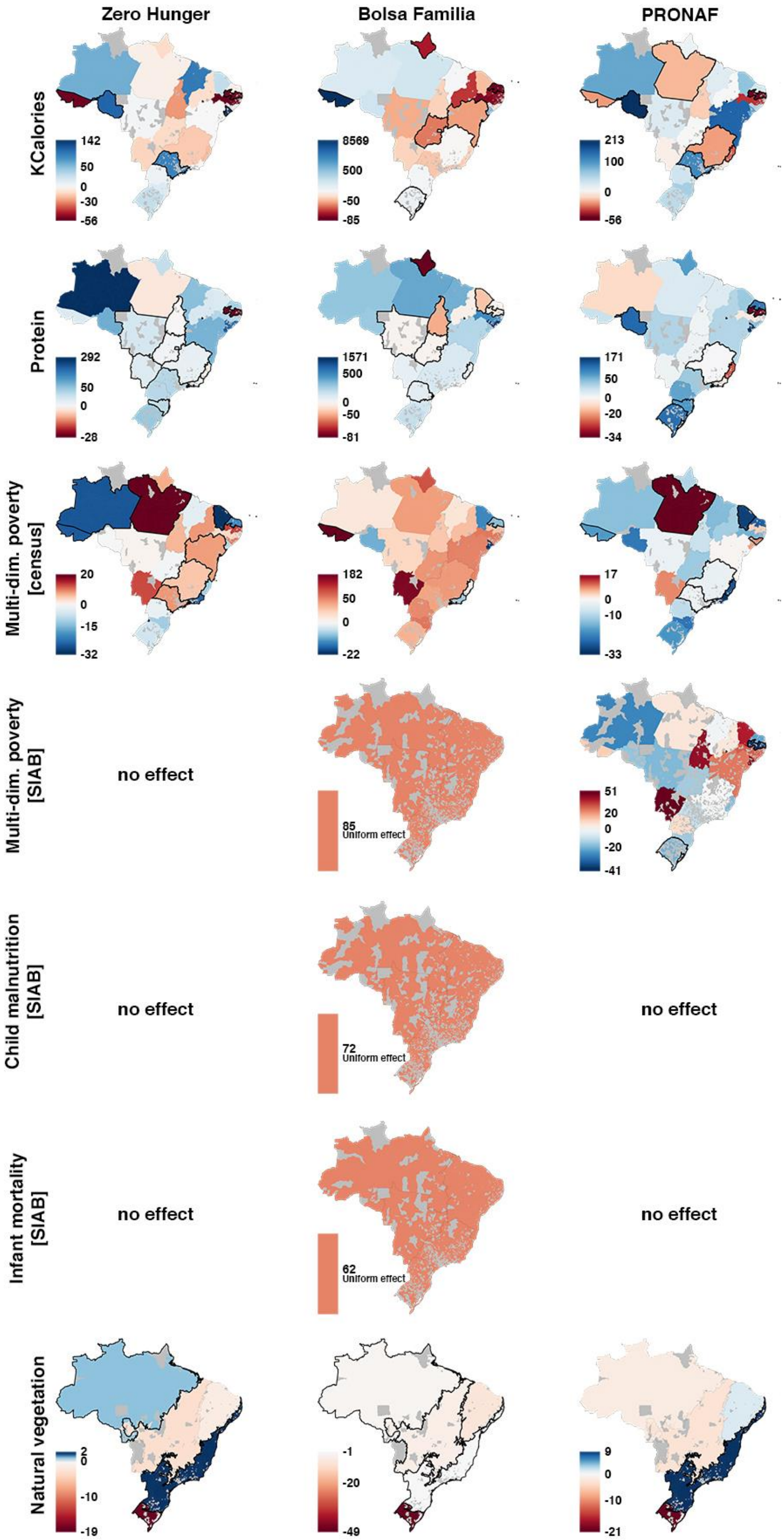
Zero Hunger
Bolsa Familia
PRONAF
KCalories
142
50
0
-30
-56
8569
500
-50
-85
213
100
0
-56
Protein
292
50
0
-28
1571
500
0
-50
-81
171
50
0
-20
-34
Multi-dim. poverty [census]
20
0
-15
-32
182
50
0
-22
17
0
-10
-33
Multi-dim. poverty [SIAB]
no effect
85
Uniform effect
51
20
0
-20
-41
Child malnutrition [SIAB]
no effect
72
Uniform effect
no effect
Infant mortality [SIAB]
no effect
62
Uniform effect
no effect
Natural vegetation
2
0
-10
-19
-1
-20
-49
9
0
-10
-21

Fig. S2. Relative impact of Zero Hunger, Bolsa Familia and PRONAF investment given a spatially uniform investment level (column 1-3) on daily per capita kilocalorie production, daily per capita protein production, multi-dimensional poverty in the entire population (Census), multi-dimensional poverty in the poorer sectors of society (SIAB), child malnutrition in the poorer sectors of society (SIAB) and natural vegetation cover (km^2) (row 1-6). Relative impact is defined as the relative change between outcome given a spatially uniform negligible (1st percentile value) program investment level and a spatially uniform median program investment level investment level. Relative impact calculations are based on robust multivariable regression models of a covariate-balanced sample (Table 1) that take confounding factors into account including interactions between investment and state, or (in the natural vegetation cover model) investment and biome. States and biomes with significantly different outcomes to the overall effect are indicated by thick black borders; thin black border show region borders (row 1-5) and ecological biome borders (row 6). We use a normative colour scheme, with blue indicating beneficial and red non-beneficial impacts, grey areas signify municipalities not included in the analysis because they were urban, or has insufficient data or fall within the model reference state/biome for which no model statistics are available

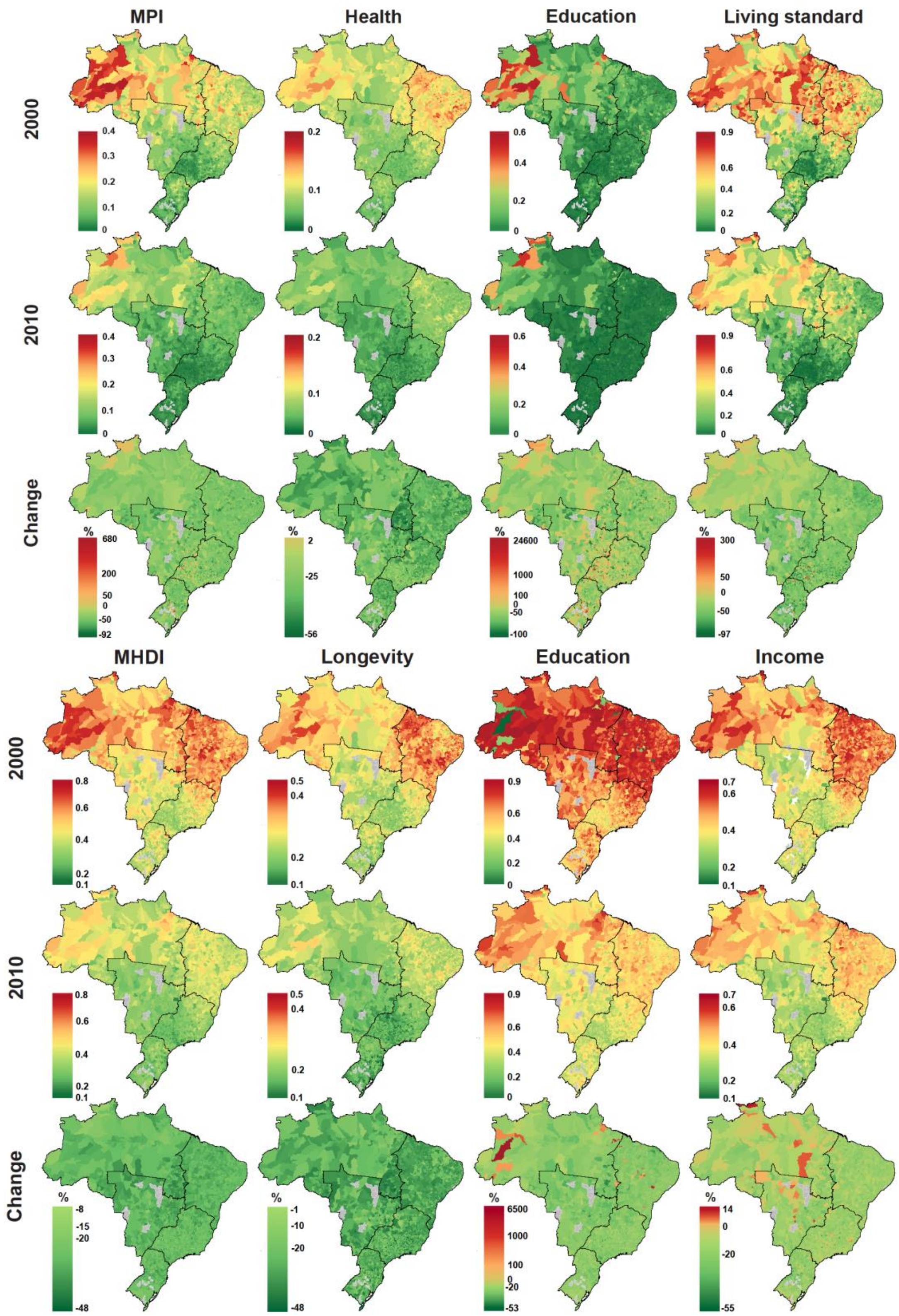

Fig. S3. High consistency between multi-dimensional poverty (census) (MPI) overall and its three dimensions Health, Education and Living Standard for 2000 and 2010 (top 3 rows), and the Brazilian Municipal Human Development Index (MHDI) (when negatively loaded) and its three dimensions Longevity, Education and Income (bottom 3 rows). The largest discrepancies are found in Education as MPI only considers education for children age 7-14 and the MHDI the whole population (Spearmans's rho for education is 0.65 and 0.39, for 2000 and 2010, respectively). The other dimensions show great similarities (r = 0.78-0.99). Overall the MPI and MHDI correlate well with r = 0.9 and 0.84 for 2000 and 2010, respectively

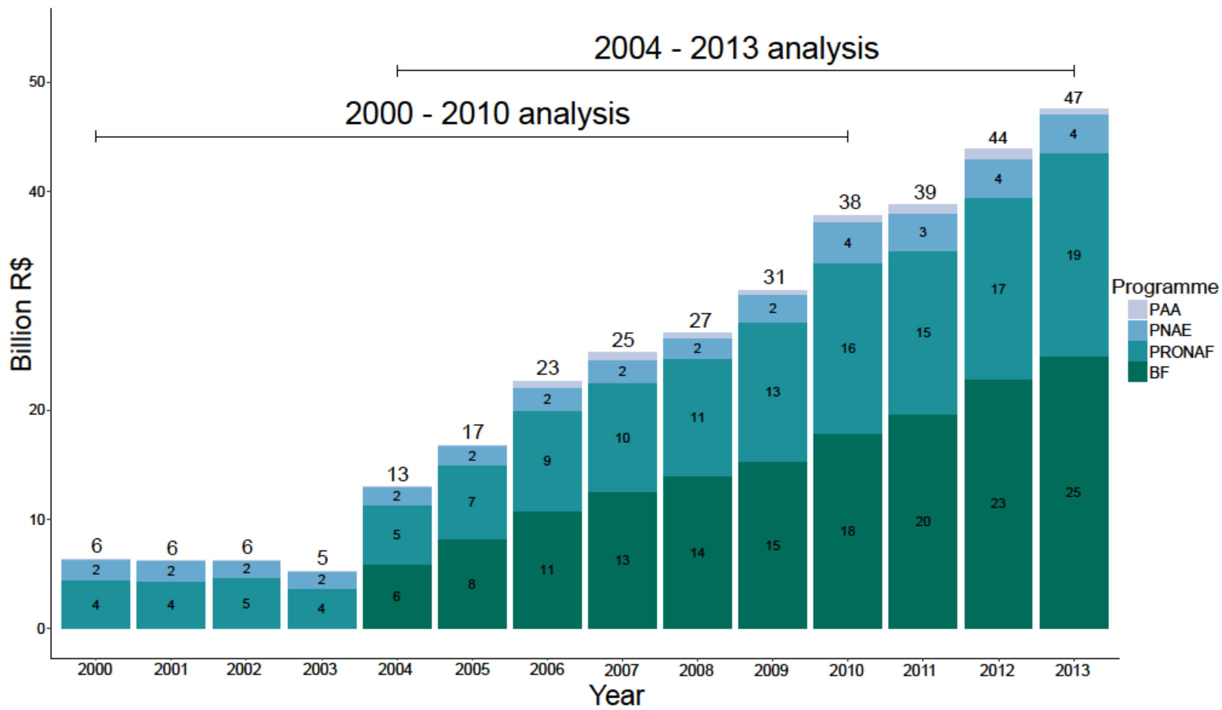

Fig. S4. Annual investments in the four main Zero Hunger (ZH) sub-programs Bolsa Familia (BF), PRONAF, PNAE and PAA available at www.dados.gov.br/www.mds.gov.br, showing a gradual increase in annual investments and predominance of BF and PRONAF to a summed ZH investment. Horizontal lines indicate investment values included in the respective 2000-2010 and 2004-2013 analyses. All values are expressed in billion Reals (R$) and adjusted for inflation with base year 2013

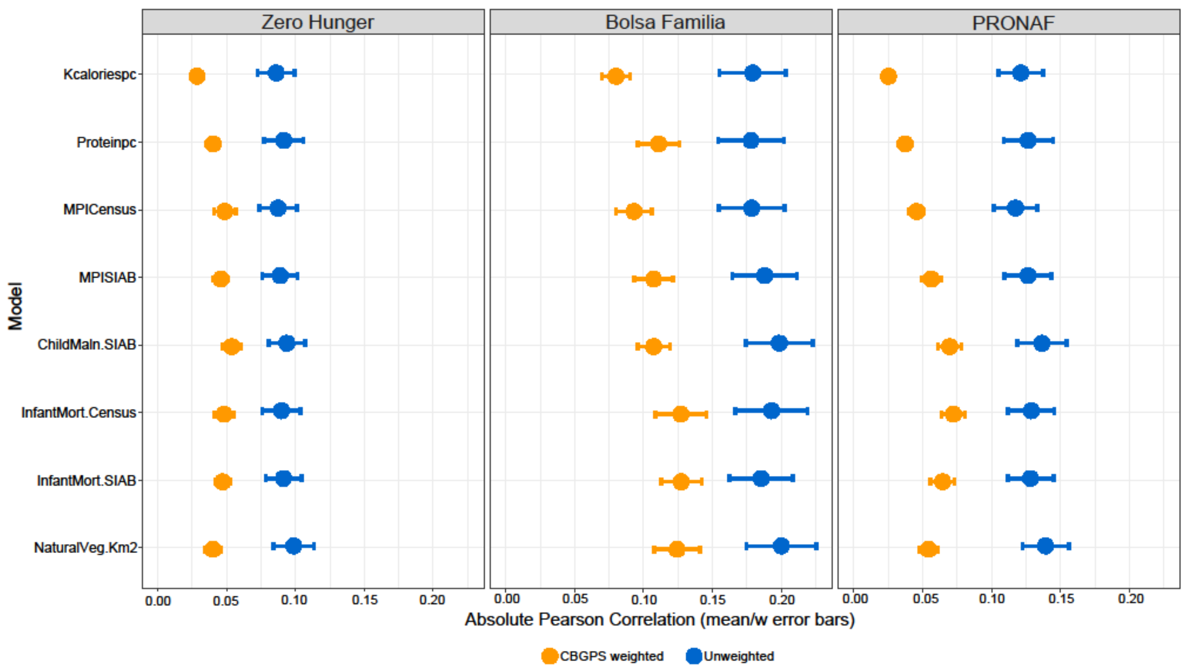

Fig. S5. Great covariate balance achieved following the Covariate balancing generalized propensity score (CBGPS) method from Fong et al. (50). Orange circles shows average absolute Pearson correlation between the Zero Hunger, Bolsa Familia and PRONAF investment variable and model covariates (predictor variables) for all models when CBGPS weights are included in the model. Blue circles are the unweighted average correlations. Lines represent error bars.

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