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

Cecilie Dyngeland[1], Johan A Oldekop[2], Karl L Evans[1]

[1]Department of Animal and Plant Sciences, The University of Sheffield, Sheffield S10 2TN, UK

[2]Global Development Institute, The University of Manchester, Manchester M13 9PL, UK

Address correspondence to: [Cecilie Dyngeland, cecidy85@gmail.com]

Abstract

Examining linkages among multiple sustainable development outcomes is key for understanding sustainability transitions. Yet rigorous evidence on multiple social and environmental outcomes of sustainable development policies remains scarce. We conduct a national-level analysis of Brazil's flagship social protection program, Zero Hunger, which aims to alleviate food insecurity and poverty. Using data from rural municipalities across Brazil and quasi-experimental causal inference techniques, to control for non-random treatment allocation, we assess relationships between investment and outcomes related to inter-linked sustainable development goals (SDGs): 'no poverty' (SDG 1), 'zero hunger' (SDG 2) and 'health and well-being' (SDG 3). We also assess potential perverse outcomes arising from agricultural development adversely impacting 'climate action' (SDG 13) and 'life on land' (SDG 15) via clearance of natural vegetation. Despite increasing daily per capita protein and kilocalorie production, summed ZH investment did not alleviate child malnutrition or infant mortality, and negligibly influenced multi-dimensional poverty. Effects on natural vegetation loss varied; higher investment increased cover in some biomes but increased losses in the Cerrado and especially the Pampa. Effects varied substantially across sub-programs. Conditional cash-transfer (Bolsa Familia) was mainly associated with non-beneficial impacts, but increased protein production and improved educational participation in some states. The agricultural-supportive PRONAF was typically associated with increased food production (protein and calories), multi-dimensional poverty alleviation and changes in natural vegetation. Our results inform policy development by highlighting successful elements of Brazil's Zero Hunger program, variable outcomes across divergent food security dimensions, and synergies and trade-offs between multiple sustainable development goals, including environmental protection.

Key words: Rural development, environmental impact, food security, Impact estimation, Land use change

Significance statement

Meeting sustainable development goals (SDGs) requires assessing trade-offs and synergies across divergent goals and robust policy impact evaluation. Using quasi-experimental inference methods, we assess impacts of Brazil's Zero Hunger (ZH) social protection programs. ZH investment increased per capita calorie and protein production. Social impacts (multi-dimensional poverty, child malnutrition and infant mortality) were more limited and the direction of change in natural vegetation cover was biome specific. Conditional cash transfer (Bolsa Familia) generated fewer benefits and more trade-offs than agricultural support (PRONAF). Results inform policy development, including roll out of ZH inspired programs in sub-Saharan Africa. We highlight successful elements of social protection programs, and synergies and trade-offs between multiple SDGs including environmental protection.

Introduction. Sustainability is an elusive societal goal requiring transitions across multiple dimensions - including food security, poverty alleviation, health and environmental protection (1). These major global challenges are interrelated (2), and are reflected in national and international development agendas, including the Sustainable Development Goals (SDGs) (3).

Food insecurity (SDG 2) remains an intractable global problem (4). Addressing it requires meeting multiple objectives simultaneously: enough healthy and nutritionally diverse food needs to be produced and available at all times to a population with physical and economic access to it (5). Food security is directly linked to poverty alleviation (SDG 1), and health and well-being (SDG 3) (6). However, agricultural production is also a key driver of natural vegetation and biodiversity loss (conflicting with SDG 15), and greenhouse gas emissions (conflicting with SDG 13) (7, 8).

Understanding synergies and trade-offs among multiple sustainability objectives, and how they are influenced by policy interventions has been a key focus of scholarly and policy discussions around the globe (9). Despite recent methodological advances in causal impact estimation empirical research which quantifies synergies and trade-offs among diverse social and environmental outcomes from poverty alleviation programs is still extremely rare (10). There is a marked and urgent need for such studies to ensure that the impacts of development programs across the range of intended and unintended sustainable development outcomes are quantified and considered when formulating policy. We address this gap by assessing how Brazil's flagship Zero Hunger (ZH) social protection programs have affected food production, multi-dimensional poverty, child malnutrition and infant mortality, and changes in natural vegetation cover. National development strategies frequently implement social protection programs to support livelihoods, alleviate income or food poverty, and manage vulnerability to shocks (11). Programs are often designed and evaluated as single instruments. A crucial part of any program evaluation is assessing whether program objectives are met, but programs rarely asses secondary outcomes that are not core objectives (12). This restricted focus increases the risk that trade-offs and perverse outcomes remain undetected, potentially generating incomplete conclusions on program effectiveness (13).

In our assessment of ZH's social protection programs, we leverage a suite of high spatial resolution datasets, and use a quasi-experimental approach that combines covariate balancing weights with multiple regression analyses to help control for potential non-random program implementation. Our analysis provides novel insights on how to achieve multiple sustainability outcomes, and is directly relevant to the design and implementation of social protection mechanisms in other regions of the world, particularly sub-Saharan Africa, where several programs are partly based on ZH (14).

Brazil's Zero Hunger Program. The ZH program aimed to lift 44 million poor Brazilians out of poverty and food insecurity and was fully implemented in 2004 (15). Four sub-programs formed the core of ZH, and at its inception received ~90% of ZH's total budget (15). ZH has since evolved into other initiatives (Brasil Sem Miseria, i.e. Brazil without extreme poverty) that continue to operate these four sub-programs with national government funding allocated to state or municipal governments, and in some instances directly to program beneficiaries. Small-scale family farmers are the programs' primary target beneficiaries, due to their key role in rural development and national food security (16, 17). They are provided with i) low interest agricultural credits through *The National Program to Strengthen Family Farming* (PRONAF) and, ii) access to price-controlled markets through *The Food Acquisition Program* (PAA). The markets created through PAA are operated by state-linked institutions that buy produce directly from local farmers to supply social assistance programs, government funded schools and local markets (15). A key social assistance program is iii) *The National School Feeding Program* (PNAE) which provides free school meals to all children and promotes the use of produce from family farms (15). Finally, families in poverty, many of which are small-scale farmers, qualify for monthly cash transfers through iv) *The Bolsa Familia* (BF) sub-program, conditional on child school attendance and participation in family health checks and vaccination programs (although families without children can also get support) (15). ZH and core sub-programs predate the SDGs, and do not combine objectives focused on protecting the natural environment or climate change mitigation with its objectives concerning food production and poverty. Nevertheless, these programs form an integrated large-scale initiative with the potential to influence both social and environmental dimensions captured in the SDGs framework, including rural livelihoods and food security, health outcomes, agricultural production, and land-use change. Assessing ZH and its contribution to multiple outcomes – both intended (food security, poverty and health) and unintended (environmental) – is thus vital to get a full understanding of its contribution to transitions towards sustainability (10).

ZH programs have been associated with increased farm incomes and productivity (18–20), increases in agrobiodiversity (21), increased food purchases in food insecure households (22), reduced child malnutrition (23, 24), and lower infant mortality (25, 26). Yet, contrasting evidence suggests that ZH programs have had negligible effects on agricultural production, farmer livelihoods, child malnutrition and long-term food security (27–30), and have failed to reach the poorest and most vulnerable families (31–33). However, the majority of ZH impact studies assess impacts on individual treated and untreated households. They thus focus exclusively on micro-scale pathways that generate benefits, ignoring the larger scale indirect pathways through which benefits can accrue (e.g. impacts of market stimulation on untreated households (34)). Assessing aggregate impacts over larger geographic scales enables us to: first - capture potential impacts arising from investment in ZH at the cost of reduced investment in other initiatives (e.g. basic infrastructure (35)); and second - account for impacts of expansion of agricultural activities beyond the boundaries of household land parcels. Previous studies are also limited by a failure to consider spatial heterogeneities, and/or key confounding factors, and have focused on a narrow range of outcomes that prevent full exploration of synergies and trade-offs across multiple sustainable development objectives.

Analytical approach. We assess ZH effects on food production, multi-dimensional poverty, health and changes in natural vegetation cover using a quasi-experimental approach and municipal level publicly available data from national and global sources (see Materials and Methods). We created a high-spatial resolution longitudinal dataset for rural municipalities across Brazil (n = 3786-4976, i.e. 74-97% of all rural municipalities – sample sizes were outcome and program component dependent). We focus on rural areas because this is where family farmers (one of ZH's primary beneficiaries) are overwhelmingly concentrated, and because impacts are likely to be heterogeneous across urban and rural areas. We first analyse the impact of summed financial investment across ZH's main sub-programs (PRONAF, PAA, PNAE and BF), and then separately assess the impacts of the two largest sub-programs, BF and PRONAF, which captured respectively 46% and 42% of ZH's summed investment between 2004 and 2013. These sub-programs are examples of the types of social protection programs that are frequently implemented elsewhere: conditional cash transfer to protect minimum subsistence (BF), and credit provision to support household investment and livelihood diversification (PRONAF) (11).

We assess impact on changes in multi-dimensional poverty (SDG 1), food production (daily per capita Kcalorie and protein production; SDG 2), child malnutrition (proportion of underweight infants and children age 12-24 months; SDGs 2 & 3), infant mortality (children <1 year; (SDGs 2 & 3) and area (km^2) under natural vegetation cover (SDGs 13 & 15). For all outcomes we measure change from 2004 (the first complete year of ZH implementation) to 2013 (at the time of analysis the most recent year with information across all predictor variables). We use two separate datasets for multi-dimensional poverty and infant mortality that represent i) the poorest sub-sample of each municipality's population using data from the national primary information system (SIAB) (change assessed 2004-2013) (36), and ii) the entire municipal population using the national demographic census (due to census dates assessing change from 2000 to 2010).

We combine covariate balancing generalized propensity score weights (CBGPS method (37)) with multiple regression analyses to assess links between investment and changes in outcomes. This helps limit potential non-random treatment allocation bias by reducing the correlation between treatment and potential confounding factors (37) (Materials and Methods and "SI Appendix; CBGPS"). We model outcomes in the final year of the evaluation period as a function of summed per capita investment in ZH (R$). We account for inflation (IGP-DI index, base year 2013), and control for 15 key biophysical and socio-economic factors and baseline conditions, including variables that affect the implementation of ZH and its sub-programs (Materials and Methods and "SI Appendix; Confounding variables; Table S1 and Table S2").

Our statistical regression models include interactions between investment, and state or biome to account for potential spatial variation in program implementation, and differential outcomes in divergent environments. We use our regression models to predict changes in outcomes resulting from three different investment scenarios: negligible investment (defined as the 1st percentile of investment values to avoid using zero values that would predict beyond the data range), actual investment, and a spatially uniform investment (defined as the median investment value). We map predicted percentage change in outcomes per municipality (arising from actual and spatially uniform investment) relative to a negligible investment scenario to visualize impacts across Brazil. We conduct several robustness tests to assess if our inferences still apply when excluding lower quality data - defined as municipalities with: i) extremely large areas (>10,000 km^2) that are likely to have less representative socio-economic data (38), ii) SIAB data that do not meet quality criteria defined by the Ministry of Health (39), or iii) natural vegetation data that cover less than 95% of the municipality's area due to cloud cover in 2004 or 2013. Controlling for data quality in our natural vegetation robustness models leads to the exclusion of 77% and 99.7% of the Amazon and Pantanal biomes' area. We therefore exclude these biomes from our robustness tests. We focus on results from models that use all data when these are qualitatively similar to those from models that exclude lower quality data, and in the few cases where discrepancies arise focus on results from the latter. We also check, and confirm, that our results are not unduly influenced by spatial autocorrelation or endogeneity (Materials and Methods and "SI Appendix; Robustness tests").

Results. We find considerable heterogeneity in the effects of ZH investment. This variation arises for three primary reasons. First, impacts are outcome specific with evidence of positive, negligible and negative effects. Second, within a single outcome, impacts depended on whether investment is delivered via conditional cash transfers (BF) or agricultural credits (PRONAF). Finally, within a single outcome variable and investment mechanism, there is often considerable spatial variation in the magnitude and direction of effects (Fig. 1). This is often not simply due to spatial variation in investment levels (Fig. S1), as marked spatial variation in outcomes frequently remains when modelling outcomes using a spatially uniform investment level (Fig. S2).

Food production. Summed investment across ZH sub-programs increased protein production across Brazil, while investment increased Kcalorie production in three states (Rondonia in the north, Sergipe in the north-east, and Sao Paulo in the south-east) and reduced in two (Acre in the north and Paraiba in the north-east) (Table 1; Fig. 1). Substantial spatial variation in outcomes is partially driven by differing investment levels (Fig. S1), as regional variation is reduced when keeping investment levels spatially uniform (Fig. 1 and Fig. S2), as well as trade-offs between Kcalorie and protein production arising primarily from BF investment.

Across most of Brazil, PRONAF investment was associated with increased protein (mean predicted change per municipality = 41.0%, S.E. = 0.9 compared to the negligible investment scenario; mean increase = 597.0 grams per capita per day, S.E. = 25.7) and Kcalorie production (mean predicted change per municipality = 32.8%, S.E. = 0.9; mean increase = 37,668 Kcalories per capita per day, S.E. = 2,601). Although when excluding lower quality data investment only generated a significant increase in Kcalorie production in three states (Rondonia in the north, Bahia in the north-east and Sao Paulo in the south-east) and investment significantly reduced production in four states (Acre and Para in the north, Paraiaba in the north-east and Espirito Santo in the south-east). While percentage increases in production are more marked in southern Brazil (Fig. 1), this is linked to higher investment levels in this region (Fig. S1): using spatially uniform investments levels PRONAF increases protein and Kcalorie production in the north-east at a similar rate to the south, albeit from a lower base (Fig. S2). This is notable as the north-east region has difficult climatic (hot and dry) and socio-economic conditions, and low productivity of family farms (40, 41). While family farmers in southern Brazil have participated more actively in larger national and international markets (42), e.g. for soybean, rice and beef (43), family farmers in the north-east are generally poorer (42) but contribute greatly to local and national production of staple foods such as rice, maize and cassava (40). Diverting some PRONAF funds from the south to the north-east could thus deliver cost-effective national improvements in local food production targeted at regions with the greatest need, and address a key critique that PRONAF favours wealthier farmers producing commodity products in the south (32).

BF also increased protein production (mean predicted change per municipality = 168.1%, S.E. = 8.8 per municipality; mean increase = 282.9 grams per capita per day, S.E. = 20.0). Rates of increase appear to be greater in north-eastern states (e.g. Alagoas), where baseline production was low (Fig. 1) and food insecurity has been historically high (16). BF impacts probably arise because conditional cash transfer increase incomes in poor agricultural households by up to 46% (44). These can either facilitate investment in agricultural production (as observed for cash-transfer programs in Mexico (45)) or stimulate food markets and increase local production due to increased purchasing power.

Despite positive BF effects on protein production, we find no overall effect of BF on Kcalorie production. We find, however, four states with BF-linked reductions in Kcalorie production (Amapa in the north, Bahia and Rio Grande do Norte in the north-east and Goias in the centre-west), and two states with BF-linked Kcalorie increases (Acre in the north and Rio Grande do Sul in the south; Fig 1). These spatial patterns persist when modelling impacts using spatially uniform investments (Fig. S2). One reason why BF investment may not have increased Kcalorie production may be that some farmers have used BF investment to switch from production of staple crops to protein production. To explore this potential mechanism we assess rice and cassava production (which are the main high Kcalorie crops), and milk and poultry production (which are the main high-protein products generated by Brazilian small scale farmers and used for local human consumption (16, 46). We find that total rice and cassava production have declined by 45% in the north-east, 65% in the centre-west, and 30% in the south-east. We also find that total milk and poultry production increased in the north-east (milk = 26%; poultry = 14%), centre-west (milk = 19%; poultry = 17%) and south-east (milk = 15%; poultry = 38%). Use of cash transfers to purchase rather than produce food is another potential mechanism for the declines in crop production (29, 30), especially when falling food prices (due to increases in agricultural productivity, primarily by large-scale agro-businesses) increase purchasing power of money received through cash transfers especially for low income populations (47), while simultaneously reducing the profitability of small scale production of staple crops. Regardless of the mechanism, BF does not seem to increase local production of stable crops, and at worse it may reduce it, which could reduce food security resilience to any future price shocks (2).

Multi-dimensional poverty index (MPI). We analyse two multi-dimensional poverty measures capturing information on living standards, health, and education. Our first measure uses data from the poorest sub-sample of the population (SIAB), while the second captures the municipality's entire population (census). SIAB derived multi-dimensional poverty is not associated with summed ZH investment across sub-programs, and effects of PRONAF investment are also negligible (Fig. 1, Table S3). BF investment is associated with increased SIAB derived multi-dimensional poverty (Table 1; mean predicted change per municipality = 80.7%, S.E. = 0.5; mean increase = 0.026 MPI, S.E. = 0.0003), however, when lower quality data are excluded a significant increase in SIAB derived multi-dimensional poverty only remains in two states (Mato Grosso and Sao Paulo).

It is clear that BF has had limited capacity to alleviate multi-dimensional poverty and in some regions is associated with increased poverty – these findings are counter to expectations (25, 48), but our robustness tests strongly suggest that they do not arise due to hidden bias generated by unmeasured confounding factors ("SI Appendix; Robustness tests"). Indeed, previous studies suggest that until 2010, BF support did not reach 1.2 million eligible families, and those that did receive support obtained insufficient funds to lift them out of poverty (44). Moreover, our results are compatible with a sub-national case study showing that BF was associated with increased child malnutrition, which is part of our SIAB derived multi-dimensional poverty measure (27). Notably, BF support is conditional on child school attendance, and we do find that BF investment is associated with improvements in the educational dimension of our SIAB derived multi-dimensional poverty measure in two states (Parana and Santa Catarina: Table S4). These positive impacts, whilst more limited, match those of previous research (49), and suggests that conditional cash transfers dependent on participation in education can support the educational targets of SDG 4.

There is little evidence that summed investment across ZH sub-programs is associated with notable improvements in our census derived multi-dimensional poverty metric. Whilst, when lower quality data are excluded ZH investment is significantly associated with a multi-dimensional poverty reduction, the overall effect is very small (mean predicted change = 1.9%, S.E. = 0.2 per municipality; mean reduction = 0.002 MPI, S.E. = 0.0001). When all data are included in the models there is an approximate balance in the number of states with investment associated reductions in multi-dimensional poverty (5 states: Acre and Amazonas in the north, Ceara and Rio Grande do Norte in the north-east, and Rio de Janeiro in the south-east) and poverty increases (4 states: Para in the north, Bahia in the north-east, and Minas Gerais and Sao Paulo in south-east; Fig. 1).

BF investment is generally associated with increases in census derived multi-dimensional poverty (mean predicted change = 34.7%, S.E. = 0.9 per municipality; mean increase = 0.013 MPI, S.E.

= 0.0002 per municipality) and only one state exhibiting significant poverty alleviation in response to BF investment in both the core and robust model (Fig 1 and "SI Appendix; Robustness tests"). BF investment, however, is linked to significant improvements in the educational dimension of our census derived multi-dimensional poverty measure in some states (Para and Rondonia in the north, and Alagoas and Bahia in the north-east: Table S4).

Our results suggest that the effectiveness of BF on multi-dimensional aspects of poverty, other than educational benefits in some states, are constrained across much of Brazil. There are numerous possible mechanisms for this. First, supply-side constraints may play a role, especially insufficient access to health services (50), and a lack of monitoring of the health and nutritional status of beneficiary families (e.g. between 2005 and 2012, 3.2 million BF households remained unmonitored (51)). Notably these constraints have been reported to be less marked in north-eastern Brazil (52), which is where we find some evidence that BF alleviates (census derived) multi-dimensional poverty. Second, the increased taxation that is required to fund BF is disproportionately allocated to the poorer sectors of society, thus increasing fiscal poverty amongst some BF participants (53) that reduces their capacity to purchase assets that contribute to our measure of multi-dimensional poverty. Finally, insufficient access to labour markets or longer-term financial security, e.g. through pensions, may also limit BF's ability to reduce multi-dimensional poverty (44).

In contrast to BF, we find that PRONAF investment was associated with an overall reduction in our census derived multi-dimensional poverty measure (Table 1; mean predicted change per municipality = 9.7%, S.E. = 0.2; mean reduction = 0.006 MPI, S.E. = 0.0001). The largest reductions, measured in terms of percentage change, occur in southern Brazil (22.2%, S.E. = 0.3) (Fig. 1). This is not due to higher investment as this spatial pattern remains under a uniform investment scenario (Fig. S2), and is probably influenced by the lower census derived multi-dimensional poverty baselines in this region (Fig. 1), which increase rates of change expressed as percentages.

PRONAF funds must be invested in agricultural production. This investment could lead to increases in farm employment opportunities, or stimulate labour markets associated with the production and sale of agricultural materials and equipment. Wealthier and more competitive farmers tend to be better placed than poorer farmers to benefit from any stimulation of labour markets (54), which might help explain the observed contrasting effects between PRONAF associated improvements in census derived multi-dimensional poverty, and the negligible effects in the SIAB derived multi-dimensional poverty measure.

Infant mortality and child malnutrition. The only detected effect of ZH investment on infant mortality is that BF investment is associated with increased SIAB derived infant mortality (mean predicted change = 59.4%, S.E. = 0.4 per municipality; mean increase = 725.4 deaths per 100,000 live births, S.E. = 5.9 per municipality; Table 1). These effects were not detectable, however, when we exclude lower quality data (Table S3). Increased child malnutrition, for which data are only available from the poorest sub-sample (SIAB), is also associated with social security (BF) investment (mean predicted change = 67.7%, S.E. = 0.4 per municipality; mean increase = 103.4 underweight children per 10,000 weighed children, S.E. = 1.2 per municipality; Table 1).

In combination our results provide strong evidence that investment in ZH programs is not alleviating SIAB derived child malnutrition, or census or SIAB derived infant mortality. Our findings extend earlier work conducted at local scales (27, 29, 50) to the national scale, though studies with beneficial associations between BF and child health also exist (25, 26). The lack of improvements in response to BF investment are compatible with, and may partly be driven by, higher multi-dimensional poverty levels and reduced per capita calorie production from staple crops, which we also find are associated with higher BF investment. Lack of improvements from BF investment may also be linked to insufficient monitoring and resultant intervention of the health and nutritional status of beneficiary families (see above), perhaps due to diversion of funding away from municipal institutions in charge of monitoring (55) or investments in basic infrastructure (e.g. education, health centres and public sanitation systems) (35, 56). Such infrastructure is still insufficient in many rural areas (57) and particularly amongst BF recipients (58), but is important for BF and conditional cash transfers to be effective (59). Similarly, the lack of beneficial impacts on child malnutrition and infant mortality arising from PRONAF investment occur despite PRONAF delivering substantial improvements in per capita food production.

This is unlikely a result of food unavailability due to export away from local markets since the share of family farm produce exported abroad is minimal (0.04% of temporary crops and 0.07% of permanent crops in 2006 (60)) and again probably arises due to poor access to health services and basic infrastructure for this sector of society, and perhaps limited participation in PRONAF amongst poorer and more vulnerable farmers (32).

Natural vegetation cover. Summed investment across ZH sub-programs is associated with increased natural vegetation cover in *the Amazon* (per municipality mean predicted change = 0.9%, S.E. = 0.01; mean predicted increase = 53.9 km^2, S.E. = 5.0; summed predicted increase = 24,434 km^2 across 454 municipalities), *Atlantic forest* (per municipality mean predicted change = 2.4%, S.E. = 0.02; mean predicted increase = 2.5 km^2, S.E. = 0.1; summed predicted increase = 5,826 km^2 across 2,337 municipalities) and *Caatinga* (per municipality mean predicted change = 0.6%, S.E. = 0.003; mean predicted increase = 2.9 km^2, S.E. = 0.1; summed predicted increase = 2,210 km^2 across 772 municipalities, Caatinga predictions are from the model excluding lower quality data due to a change in the direction of effect compared to a model that uses all data irrespective of quality (Table 1; Table S3; Fig. 1). In contrast, summed ZH investment is associated with natural vegetation loss in the *Cerrado* (per municipality mean predicted change = 2.8%, S.E. = 0.04; mean loss = 30.9 km^2, S.E. = 1.6; summed predicted loss = 30,844 km^2 across 1,020 municipalities) and *Pampa* (per municipality mean predicted change = 19.9%, S.E. = 0.8; mean loss = 122.6 km^2, S.E. = 13.9; summed predicted loss = 11,155 km^2 across 92 municipalities).

The direction of the effect of PRONAF investment on natural vegetation cover was the same as impacts of summed investment (ZH) in all biomes except in the Amazon where PRONAF investment was associated with deforestation (mean predicted change = 1.6%, S.E. = 0.03 per municipality; mean decrease = 96.3 km^2, S.E. = 9.6 per municipality; summed predicted decrease = 42,863 km2 across 454 municipalities). PRONAF investment was associated with natural vegetation gains in the *Atlantic forest* (per municipality mean predicted change = 9.7%, S.E. = 0.1; mean increase = 9.7 km^2, S.E. = 0.3; summed predicted increase = 22,316 km^2 across 2,337 municipalities) and *Caatinga* (per municipality mean predicted change = 1.2%, S.E. = 0.01; mean increase = 5.5 km^2, S.E. = 0.2; summed predicted increase = 5,594 km^2 across 1,015 municipalities). In contrast, PRONAF investment was associated with natural vegetation losses in the *Cerrado* (per municipality mean predicted change = 3.0%, S.E. = 0.03; mean loss = 30.8 km^2, S.E. = 1.6; summed predicted loss = 31,030 km^2 across 1,020 municipalities) and *Pampa* (per municipality mean predicted change = 23.9, S.E. = 0.6; mean loss = 158.5 km^2, S.E. = 17.3; summed predicted loss = 14,427 km^2 across 92 municipalities). When the model excludes lower quality data (which means also excluding all of the Amazon and Pantanal biome) PRONAF loses its overall significant effect. The effect of investment in the Caatinga and Cerrado also become non-significant and is reduced to less than a one percent average predicted change, however, the significant gains of natural vegetation in the Atlantic Forest remains.

BF is associated with natural vegetation loss in four biomes: the *Amazon* (per municipality mean predicted change = 2.5%, S.E. = 0.02; mean loss = 181.9 km^2, S.E. = 18.3; summed predicted loss = 82,597 km^2 across 454 municipalities), the *Cerrado* (per municipality mean predicted change = 3.9%, S.E. = 0.04; mean loss = 45.0 km^2, S.E. = 2.3; summed predicted loss = 45,851 km^2 across 1,020 municipalities), *Atlantic forest* (per municipality mean predicted change = 0.9%, S.E. = 0.01; mean predicted loss = 1.2 km^2, S.E. = 0.04; summed predicted loss = 2,660 km^2 across 2,337 municipalities) and *Pampa* (per municipality mean predicted change = 42.3%, S.E. = 0.6; mean loss = 377.2 km^2, S.E. = 41.2; summed predicted loss = 34,704 km^2 across 92 municipalities). In contrast, BF investment is associated with increased natural vegetation in the *Caatinga* (per municipality mean predicted change = 0.5%, S.E. = 0.001; mean predicted increase = 2.3 km^2, S.E. = 0.1; summed predicted increase = 1,743 km^2 across 772 municipalities, Caatinga predictions are from the model excluding lower quality data due to a change in the direction of effect compared to a model that uses all data irrespective of quality Table 1; Table S3; Fig. 1). Consequently, the contrast between negative impacts of PRONAF and BF on natural vegetation in the Amazon and apparent positive impacts of summed ZH investment suggest that the more minor ZH sub-programs (i.e. PNAE and PAA) may drive positive forest transitions in the Amazon.

Our analyses focus on total change rather than fine scale spatial dynamics of loss and gain but clearly indicate that social protection programs can have divergent, and biome specific impacts on natural vegetation in biomes that support a number of endemic and globally threatened species. The Cerrado and Pampa biomes consistently lost natural vegetation as investment in summed ZH, PRONAF and BF increased, with proportional losses being particularly large in the Pampa. This conflicts with goals to maintain biodiversity (SDG 15, life on land). In other cases, investment was associated with increased natural vegetation cover, most notably PRONAF investment was associated with increased Atlantic Forest vegetation – this and other changes in woody vegetation cover will influence carbon storage and sequestration (61) and thus action to tackle climate change (SDG 13). Investment in the heavily degraded and fragmented Atlantic Forest might have promoted agricultural intensification, limiting agricultural expansion and enabling vegetation regrowth on more marginal lands. Investments in the Pampa and Cerrado, however, could have promoted agricultural expansion. Indeed, spatially explicit analyses across Brazil suggest that positive forest transitions in the Atlantic Forest are associated with agricultural intensification, whilst agricultural expansion has led to forest loss in the Cerrado (62). The greatest ZH associated losses of natural vegetation occur in the Pampa in which the flat terrain could have facilitated expansion of arable systems (soy and sugar-cane) outside the flood-plain, as this is more profitable than the low-density livestock system that dominate the region (63), and driven the loss of natural grassland – although expansion of livestock has also contributed to these losses (64). The expansion of arable crops is likely to be driven by demand from international commodity markets, which tend to drive land conversion as a result of improvements in production and profitability (2). Such agricultural expansion is likely to generate other losses of natural vegetation associated with investment in ZH, including PRONAF driven deforestation in the Amazon and BF-led vegetation losses across most of Brazil (i.e. all biomes except the Caatinga). Notably cash-transfer programs focusing on poverty alleviation have been linked to deforestation elsewhere in the Neotropics because they promote the consumption of products that require large areas of land for their production (65).

Discussion and policy recommendations. Our analysis of ZH's social protection programs reveals synergies and trade-offs across outcomes and program components. We show that increases in food production (linked to the food availability aspect of food security - SDG 2) do not lead to improvements in other food security and health measures (child malnutrition and infant mortality - SDGs 2 & 3). Multi-dimensional poverty reductions (SDG 1), when present, are modest especially for the poorer sectors of society. ZH's social protection programs have also had substantial effects on natural vegetation cover (SDGs 13 &15). Notably, the direction of these impacts vary across biomes, which is probably linked to regional differences in the capacity for investment to limit agricultural expansion and associated forest transitions. It is clear, however, when considering all outcomes that positive synergies (win-win outcomes) across divergent sustainable development goals arose more rarely than trade-offs (win-lose) and negative synergies (lose-lose) as a consequence of investment in social protection programs (Table 1; see Fig. 2 for examples). Notably positive synergies can arise across paired outcomes relating to human well-being and environmental protection (Fig. 2). This is of notable policy relevance as environmental outcomes of social protection programs are much less well understood than their impacts on people (13).

Several factors could have increased the probability that benefits of social protection programs are either limited or trade-off against additional sustainable development objectives. Access to ZH's social security programs in Brazil has not been conditional on environmental compliance – this contrasts with the Brazilian Central Bank's policy (Resolution 3,545) where rural credit conditioned on proof of environmental land registration has reduced deforestation rates in the Amazon (66). Environmental conditionalities imposed on social protection programs that encourage retention of natural vegetation on land holdings, whilst promoting farming practices that can increase yields on cultivated/grazed areas could help mitigate the trade-offs between protecting natural vegetation and food production objectives that we document. Such conditionalities would need to be coupled with mechanisms, such as agricultural extension assistance, to ensure that poorer and disadvantaged farmers (e.g. those with small land areas) are able to comply and are not discouraged from accessing social security programs. These conditionalities will not, however, curb negative environmental effects from non-recipient farmers who respond to program induced stimulation of local markets.

Conditional cash transfers (BF) are associated with improved educational metrics in a few states, but they have had limited effectiveness in alleviating multi-dimensional poverty and health benefits (a key dimension of poverty). This seems likely to have been primarily driven by a diversion of funds to cash transfers and away from the institutions and infrastructure that are also needed to deliver health improvements (35, 55, 56). Reversing this change is likely to be costly but beneficial in delivering target outcomes. Conditioning receipts of benefits on maintaining some production of staple crops could also limit a shift away from staple crop production, which has probably also contributed to limited alleviation of multi-dimensional poverty and health outcomes, and increase family farmers' resilience against price shocks.

National and local contexts need to be considered when social protection programs are designed, implemented and evaluated. Our analyses can, however, inform discussion of the ZH inspired social protection programs that currently operate in sub-Saharan Africa, (e.g. conditional cash-transfers in Ghana (67), Purchase from Africa for Africans (PAA Africa) in Ethiopia, Malawi, Mozambique, Niger, and Senegal (68), and rural credit in Zimbabwe (69)). Crop yields in these regions are typically stagnant, and are even falling in some locations, against a background of rapid rises in demand due to human population growth rates (70). Experimental and theoretical evidence, however, strongly indicate the potential for changes in agricultural practice to close yield gaps across much of sub-Saharan Africa and meet increasing demand when combined with additional intensification measures including irrigation and increased cropping frequency (71). Targeting poverty through improving market access and off-farm opportunities will also make substantial contributions to increasing food security in sub-Saharan Africa (72). ZH derived social protection programs that simultaneously tackle poverty and food production are thus well placed to contribute to tackling the region's food insecurity. This is also likely to generate health outcomes as food insecurity is a major contributor to poor health in sub-Saharan Africa (5). Our results highlight a number of factors that are likely to enhance the success of ZH inspired programs in sub-Saharan Africa and reduce trade-offs with other SDGs. Program effectiveness is likely to be particularly influenced by associated investment in health infrastructure and improved functioning of institutions, including site specific agricultural extension offices (73, 74), which are often limited in rural areas of sub-Saharan Africa (11, 75). Despite the potential to improve food production without requiring agricultural expansion that trades off against protecting natural vegetation and associated biodiversity and carbon stocks, avoidance of such negative synergies is likely to require including environmental conditionalities in social protection programs. This will also require supporting agricultural extension offices to advice on environmental aspects and institutional capacity to monitor compliance. Regular fine-scale monitoring and evaluations of interventions that consider social, economic and biophysical heterogeneity will also enhance outcomes by suggesting pathways towards program improvement during implementation cycles.

While our analyses reveal that investment in ZH may have been less successful in meeting some of its objectives than indicated by previous analyses, we provide nation-wide evidence that investment has benefitted food production, and in some regions has additionally benefitted, multi-dimensional poverty and natural vegetation, particularly from interventions providing rural credit to family farmers. Recent political changes in Brazil have led to substantial budget cuts for core sub-programs assessed in this paper (76). Our analyses indicate that these policy changes may halt or even reverse advances that Brazil has made towards increasing food availability (SDG 2), reducing poverty (SDG 1), and conserving natural vegetation and its associated benefits (SDGs 13 & 15).

Materials and Methods

Our analysis relies on a longitudinal dataset spanning the period between 2000 and 2013, and covering between 3,786 and 4,976 rural municipalities in Brazil. This dataset is constructed from publicly available national and global datasets. Our identification strategy leverages heterogeneity in investment levels in ZH and its core sub-programs (BF and PRONAF) to assess how social protection programs influence a range of key indicators linked to multiple sustainable development outcomes: multi-dimensional poverty (SDG 1), food security (SDG 2), health (SDG 3), and natural vegetation changes (relating to action to tackle climate change SDG 13 and life on land SDG 15). We conduct all our calculations in R version 3.4.2 (77), and improve the causal inference of our analysis by using a quasi-experimental design. This design uses a suite of 15 key biophysical and socioeconomic variables to control for potential factors affecting ZH investment and our outcomes of interest, and to generate a series of covariate balancing generalized propensity score weights. We also conduct a series of robustness tests to verify that our results are not unduly influenced by data quality, spatial autocorrelation, and endogeneity. Please refer to the Supplementary Information for a detailed description of our methods, including i) the construction of indicators, treatment variables, covariates and respective data sources; ii) information on our regression model specifications and quasi-experimental design; and iii) robustness tests.

Data Availability

The data and analysis code have been deposited on the Harvard Dataverse [link: both data and code will be uploaded upon acceptance].

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References.

1. J. Loos, *et al.*, Putting meaning back into "sustainable intensification." *Front. Ecol. Environ.* **12**, 356–361 (2014).
2. P. Meyfroidt, Trade-offs between environment and livelihoods: Bridging the global land use and food security discussions. *Glob. Food Sec.* **16**, 9–16 (2018).
3. United Nations, Sustainable Development Goals Knowledge Platform (2019) (September 18, 2019).
4. FAO, IFAD, UNICEF, WFP, WHO, "The State of Food Security and Nutrition in the World. Building resilience for peace and food security" (2017).
5. J. Ingram, A food systems approach to researching food security and its interactions with global environmental change. *Food Secur.* **3**, 417–431 (2011).
6. T. Benton, The many faces of food security. *Int. Aff.* **92**, 1505–1515 (2016).
7. F. N. Tubiello, *et al.*, The Contribution of Agriculture, Forestry and other Land Use activities to Global Warming, 1990-2012. *Glob. Chang. Biol.* **21**, 2655–2660 (2015).
8. T. Newbold, *et al.*, Global effects of land use on local terrestrial biodiversity. *Nature* **520**, 45–50 (2015).
9. M. Nilsson, D. Griggs, M. Visbeck, Map the interactions between SDGs. *Nature* **534**, 320–322 (2016).
10. F. Alpízar, P. J. Ferraro, The environmental effects of poverty programs and the poverty effects of environmental programs : The missing RCTs. *World Dev.* **127**, 2019–2021 (2020).
11. S. Devereux, Social protection for enhanced food security in sub-Saharan Africa. *Food Policy*

60, 52–62 (2016).

12. A. Barrientos, Social Transfers and Growth : What Do We Know ? What Do We Need to Find Out ? *World Dev.* **40**, 11–20 (2012).
13. C. Liao, D. G. Brown, Assessments of synergistic outcomes from sustainable intensification of agriculture need to include smallholder livelihoods with food production and ecosystem services. *Curr. Opin. Environ. Sustain.* **32**, 53–59 (2018).
14. M. Fraundorfer, Zero hunger for the world: Brazil´s global diffusion of its Zero Hunger strategy. *Austral Brazilian J. Strateg. Int. Relations* **2**, 91–116 (2013).
15. J. G. da Silva, M. E. Del Grossi, C. G. de França, *The Fome Zero (Zero Hunger) Program: The brazilian experience*, J. G. da Silva, M. E. Del Grossi, C. G. de França, Eds. (2011).
16. A. W. Kepple, A. Carolina, F. Silva, E. A. Fernandes, "The state of food and nutrition security in Brazil: A multi-dimensional portrait" (2014).
17. L. H. Samberg, J. S. Gerber, N. Ramankutty, M. Herrero, P. C. West, Subnational distribution of average farm size and smallholder contributions to global food production. *Environ. Res. Lett.* **11**, 1–11 (2016).
18. M. Doretto, E. Michellon, "Avaliação dos Impactos Econômicos, Sociais e Culturais do Programa de Aquisição de Alimentos no Paraná" in *Avaliação de Políticas de Aquisição de Alimentos*, 27th Ed., F. B. B. Filho, A. D. de Carvalho, Eds. (UnB/CEAM/NER, 2007), pp. 107–138.
19. F. Garcia, S. M. Helfand, A. P. Souza, "Conditional Cash Transfers and Rural Development Policies in Brazil: Exploring Potential Synergies between Bolsa Família and PRONAF" (2015).
20. M. de O. Garcias, A. L. Kassouf, Assessment of rural credit impact on land and labor productivity for Brazilian family farmers. *Nov. Econ.* **26**, 721–746 (2016).
21. V. Valencia, H. Wittman, J. Blesh, Structuring Markets for Resilient Farming Systems. *Agron. Sustain. Dev.* **39**, 1–14 (2019).
22. Agência IBASE, Repercussões do programa Bolsa Família na segurança alimentar e nutricional das Familias beneficiadas (2008).
23. A. de Brauw, D. O. Gilligan, J. Hoddinott, S. Roy, "The impact of Bolsa Familia on child, maternal, and household welfare" (2012).
24. R. Paes-Sousa, L. M. P. Santos, É. S. Miazaki, Effects of a conditional cash transfer programme on child nutrition in Brazil. *Bull. World Health Organ.* **89**, 496–503 (2011).
25. D. Rasella, R. Aquino, C. a T. Santos, R. Paes-Sousa, M. L. Barreto, Effect of a conditional cash transfer programme on childhood mortality: a nationwide analysis of Brazilian municipalities. *Lancet* **382**, 57–64 (2013).
26. E. S. de A. da Silva, N. A. Paes, Bolsa Família Programme and the reduction of child mortality in the municipalities of the Brazilian semiarid region. *Cien. Saude Colet.* **24**, 623–630 (2019).

27. J. A. Labrecque, *et al.*, Effect of a conditional cash transfer program on length-for-age and weight- for-age in Brazilian infants at 24 months using doubly-robust, targeted estimation. *Soc. Sci. Med.* **211**, 9–15 (2018).

28. J. a. Oldekop, *et al.*, Linking Brazil's food security policies to agricultural change. *Food Secur.* (2015) https:/doi.org/10.1007/s12571-015-0475-4.

29. B. A. Piperata, K. McSweeney, R. S. Murrieta, Conditional Cash Transfers, Food Security, and Health: Biocultural Insights for Poverty-Alleviation Policy from the Brazilian Amazon. *Curr. Anthropol.* **57**, 806–826 (2016).

30. K. Thorkildsen, Social-Ecological Changes in a Quilombola Community in the Atlantic Forest of Southeastern Brazil. *Hum. Ecol.* (2014) https:/doi.org/10.1007/s10745-014-9691-3 (October 13, 2014).

31. R. Paes-Sousa, J. Vaitsman, The Zero Hunger and Brazil without Extreme Poverty programs: a step forward in Brazilian social protection policy. *Cien. Saude Colet.* **19**, 4351–4360 (2014).

32. F. G. Silveira, *et al.*, "Public policies for rural development and combating poverty in rural areas" (2016).

33. A. Soares, F.V.Nehring, R.Schwengber, R.B.Rodrigues, C.G.Lambais, G.Balaban, D.S.Jones, C. , Galante, "Structured Demand and Smallholder Farmers in Brazil: the Case of PAA and PNAE" (2013).

34. OECD, *Can Social Protection Be an Engine for Inclusive Growth?*, Development Centre Studies, Ed. (OECD Publishing, 2019).

35. A. Hall, Brazil's Bolsa Familia : A Double-Edged Sword? *Dev. Change* **39**, 799–822 (2008).

36. D. Rasella, R. Aquino, M. L. Barreto, Impact of the Family Health Program on the quality of vital information and reduction of child unattended deaths in Brazil: an ecological longitudinal study. *BMC Public Health* **10**, 380 (2010).

37. C. Fong, C. Hazlett, K. Imai, Covariate Balancing Propensity Score for a Continuous Treatment : Application to the Efficacy of Political. *Forthcom. Ann. Appl. Stat.* (2017).

38. D. I. Gregorio, L. M. DeChello, H. Samociuk, M. Kulldorff, Lumping or splitting: seeking the preferred areal unit for health geography studies. *Int. J. Health Geogr.* **4**, 6 (2005).

39. Ministerio da Saude, "Sistema de Informação da Atenção Básica SIAB Indicadores 2002" (2003).

40. C. E. Guanziroli, A. Marcio, A. Di Sabbato, Dez Anos de Evolução da Agricultura Familiar no Brasil : (1996 e 2006). *Rev. Econ. e Sociol. Rural* **50**, 351–370 (2012).

41. D. Sietz, *et al.*, Smallholder agriculture in Northeast Brazil: Assessing heterogeneous human-environmental dynamics. *Reg. Environ. Chang.* **6**, 132–146 (2006).

42. L. Cabral, A. Favareto, L. Mukwereza, K. Amanor, Brazil ' s Agricultural Politics in Africa: More Food International and the Disputed Meanings of ' ' Family Farming ". *World Dev.* **81**, 47–60 (2016).

43. T. E. de Oliveira, *et al.*, Agricultural land use change in the Brazilian Pampa Biome: The reduction of natural grasslands. *Land use policy* **63**, 394–400 (2017).
44. R. G. Osorio, P. H. G. F. de Souza, S. S. D. Soares, L. F. B. de Oliveira, "Perfil da pobreza no Brasil e sua evolução no período 2004-2009" (2011).
45. J. E. Todd, P. C. Winters, T. Hertz, Conditional cash transfers and agricultural production: Lessons from the oportunidades experience in Mexico. *J. Dev. Stud.* **46**, 39–67 (2010).
46. J. L. P. Daniel, T. F. Bernardes, C. C. Jobim, P. Schmidt, L. G. Nussio, Production and utilization of silages in tropical areas with focus on Brazil. *Grass Forage Sci.* **74**, 188–200 (2019).
47. D. Arias, P. A. Vieira, E. Contini, B. Farinelli, M. Morris, "Agriculture Productivity Growth in Brazil: Recent trends and future prospects" (2017).
48. K. Lindert, A. Linder, J. Hobbs, B. de la Brière, "The Nuts and Bolts of Brazil's Bolsa Família Program: Implementing Conditional Cash Transfers in a Decentralized Context" (2007).
49. A. de Brauw, D. O. Gilligan, J. Hoddinott, S. Roy, The Impact of Bolsa Família on Schooling. *World Dev.* **70**, 303–316 (2015).
50. F. V. Soares, R. P. Ribas, R. G. Osorio, Evaluating the Impact of Brazil's Bolsa Familia: Cash transfer programs in comparative perspective. *Lat. Am. Res. Rev.* **45**, 173–190 (2010).
51. T. Cambello, M. C. Neri, *Bolsa Familia Program: a decade of social inclusion in Brazil: Executive Summary*, Tereza Campello and Marcelo Côrtes Neri, Ed. (MDS and IPEA, 2014).
52. F. R. de Araújo, M. A. D. de Araújo, F. J. V. de Souza, I. L. P. Gurgel, A. C. C. Gomes, Distribuição Espacial do Desempenho do Programa Bolsa Família: Um Estudo à Luz do IGD-M. *Rev. Ciencias Sociais, Rio Janeiro* **61**, 773–806 (2018).
53. S. Higgins, N. Lustig, Can a poverty-reducing and progressive tax and transfer system hurt the poor? *J. Dev. Econ.* **122**, 63–75 (2016).
54. S. M. Helfand, A. R. B. Moreira, E. W. B. Jr., "Agricultural Productivity and Family Farms in Brazil : Creating Opportunities and Closing Gaps" (2015).
55. W. Hunter, N. B. Sugiyama, "Assessing the Bolsa Familia: Successes, shortcomings, and unknowns" in *Democratic Brazil Divided*, P. R. Kingstone, T. J. Power, Eds. (University of Pittsburgh Press, 2017).
56. D. Sánchez-Ancochea, L. Mattei, Bolsa família, poverty and inequality: Political and economic effects in the short and long run. *Glob. Soc. Policy* **11**, 299–318 (2011).
57. S. Soares, L. De Souza, W. J. Silva, F. G. Silveira, "Poverty profile: the rural North and Northeast regions of Brazil" (2016).
58. C. F. Camargo, C. R. B. Curralero, E. C. Licio, J. Mostafa, "Perfil socioeconômico dos beneficiários do programa Bolsa Família: o que o cadastro único revela?" in *Programa Bolsa Família: Uma Década de Inclusão e Cidadania*, T. Campello, M. C. Neri, Eds. (IPEA, 2013), pp. 1–494.

59. S. Cecchini, A. Madriaga, "Conditional Cash Transfer Programmes: The recent experience in Latin America and the Carribbean" (2011).

60. S. Schneider, A. Cassol, "A agricultura familiar no Brasil" (2013).

61. C. Y. Shimamoto, P. C. Botosso, M. C. M. Marques, Forest Ecology and Management How much carbon is sequestered during the restoration of tropical forests ? Estimates from tree species in the Brazilian Atlantic forest. *For. Ecol. Manage.* **329**, 1–9 (2014).

62. A. G. O. P. Barretto, G. Berndes, G. Sparovek, S. Wirsenius, Agricultural intensification in Brazil and its effects on land-use patterns: an analysis of the 1975 – 2006 period. *Glob. Chang. Biol.* **19**, 1804–1815 (2013).

63. A. E. Arantes, V. R. de M. Couto, E. E. Sano, L. G. Ferreira, Livestock intensification potential in Brazil based on agricultural census and satellite data analysis. *Pesqui. Agropecu. Bras.* **53**, 1053–1060 (2018).

64. P. Modernel, *et al.*, Land use change and ecosystem service provision in Pampas and Campos grasslands of southern South America. *Environ. Res. Lett.* **11**, 1–22 (2016).

65. J. Alix-Garcia, C. Mcintosh, K. R. E. Sims, J. R. Welch, The Ecological Footprint of Poverty Allevation: Evidence from Mexico's Oportunidades Program. *Rev. Econ. Stat.* **95**, 417–435 (2013).

66. J. Assunção, C. Gandour, R. Rocha, R. Rocha, "The Effect of Rural Credit on Deforestation : Evidence from the Brazilian Amazon" (2016).

67. I. Costa-Leite, B. Suyama, M. Pomeroy, "Africa-Brazil co-operation in social protection Drivers , lessons and shifts in the engagement of the Brazilian Ministry of Social Development" (2013).

68. C. Milhorance, M. Bursztyn, E. Sabourin, The politics of the internationalisation of Brazil's 'Zero Hunger' instruments. *Food Secur.* **11**, 447–460 (2019).

69. F. M. Pierri, How Brazil's agrarian dynamics shape development cooperation in Africa. *IDS Bull.* **44**, 69–79 (2013).

70. D. K. Ray, N. Ramankutty, N. D. Mueller, P. C. West, J. A. Foley, Recent patterns of crop yield growth and stagnation. *Nat. Commun.* **3**, 1–7 (2012).

71. M. K. Van Ittersum, *et al.*, Can sub-Saharan Africa feed itself? *Proc. Natl. Acad. Sci.* **113**, 14964–14969 (2016).

72. R. Frelat, *et al.*, Drivers of household food availability in sub-Saharan Africa based on big data from small farms. *Proc. Natl. Acad. Sci.* **113**, 458–463 (2016).

73. C. Ragasa, J. Mazunda, The impact of agricultural extension services in the context of a heavily subsidized input system: The case of Malawi. *World Dev.* **105**, 25–47 (2018).

74. O. Oyinbo, *et al.*, Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria. *Agric. Syst.* **173**, 12–26 (2019).

75. A. R. Dorward, J. F. Kirsten, S. W. Omamo, C. Poulton, N. Vink, "Institutions and the agricultural development challenge in Africa" in *Institutional Economics Perspective on African Agricultural Development*, (IFPRI, 2009), pp. 1–34.

76. K. Doniec, R. D. Alba, L. King, Brazil ' s health catastrophe in the making. *Lancet* **392**, 731–732 (2018).

77. R Core Development Team, R: A Language Environment for Statistical Computing. *R Found. Stat. Comput.* (2018).

Table 1. Impacts of per capita summed Zero Hunger (ZH), Bolsa Familia (BF) and PRONAF investment on food production, multi-dimensional poverty, child malnutrition, infant mortality and natural vegetation cover from robust multivariable regression models of a covariate-balanced sample that take confounding factors into account.

	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)	0.002±0.04	0.958	2E-09	0.93	-0.02±0.02	0.454	1E-17	0.93	0.03±0.01	0.005	2E-54	0.94
Protein (per capita)	0.08±0.01	1E-08	1E-25	0.96	0.08±0.02	5.E-06	9E-14	0.96	0.04±0.01	3.E-06	6E-76	0.96
Multi-dim. poverty (census)	-0.01±0.01	0.144	4.E-07	0.77	0.05±0.01	6.E-07	0.001	0.79	-0.02±0.004	1.E-06	9E-09	0.77
Multi-dim. poverty (SIAB)	0.01±0.01	0.380		0.61	0.08±0.02	2.E-06		0.61	0.002±0.01	0.850	0.013	0.61
Child Malnutrition (SIAB)	0.05±0.04	0.192		n/a	0.18±0.05	4.E-04		n/a	-0.05±0.03	0.099		n/a
Infant Mortality (census)	0.01±0.24	0.961		0.13	0.05±0.22	0.805		0.14	-0.01±0.24	0.976		0.14
Infant Mortality (SIAB)	0.01±0.04	0.777		n/a	0.16±0.05	0.002		n/a	-0.02±0.04	0.660		n/a
Natural Veg. (km2)	-0.01±0.004	9.E-05	9.E-06	0.99	-0.03±0.01	9.E-05	0.004	0.99	-0.01±0.003	0.018	5.E-05	0.99

Outcomes refer to daily per capita kilocalorie and protein production, multi-dimensional poverty in the entire population (Census) and in the poorer sectors of society (SIAB), child malnutrition in the poorer sectors (SIAB), infant mortality in the entire population (Census) and the poorer sectors (SIAB), and area of natural vegetation. Model coefficients are reported ± one standard error. Interaction terms (Int.) show p-values for the interactions between investment and state in all models except 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 (census), multi-dimensional poverty (SIAB) 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 (19).

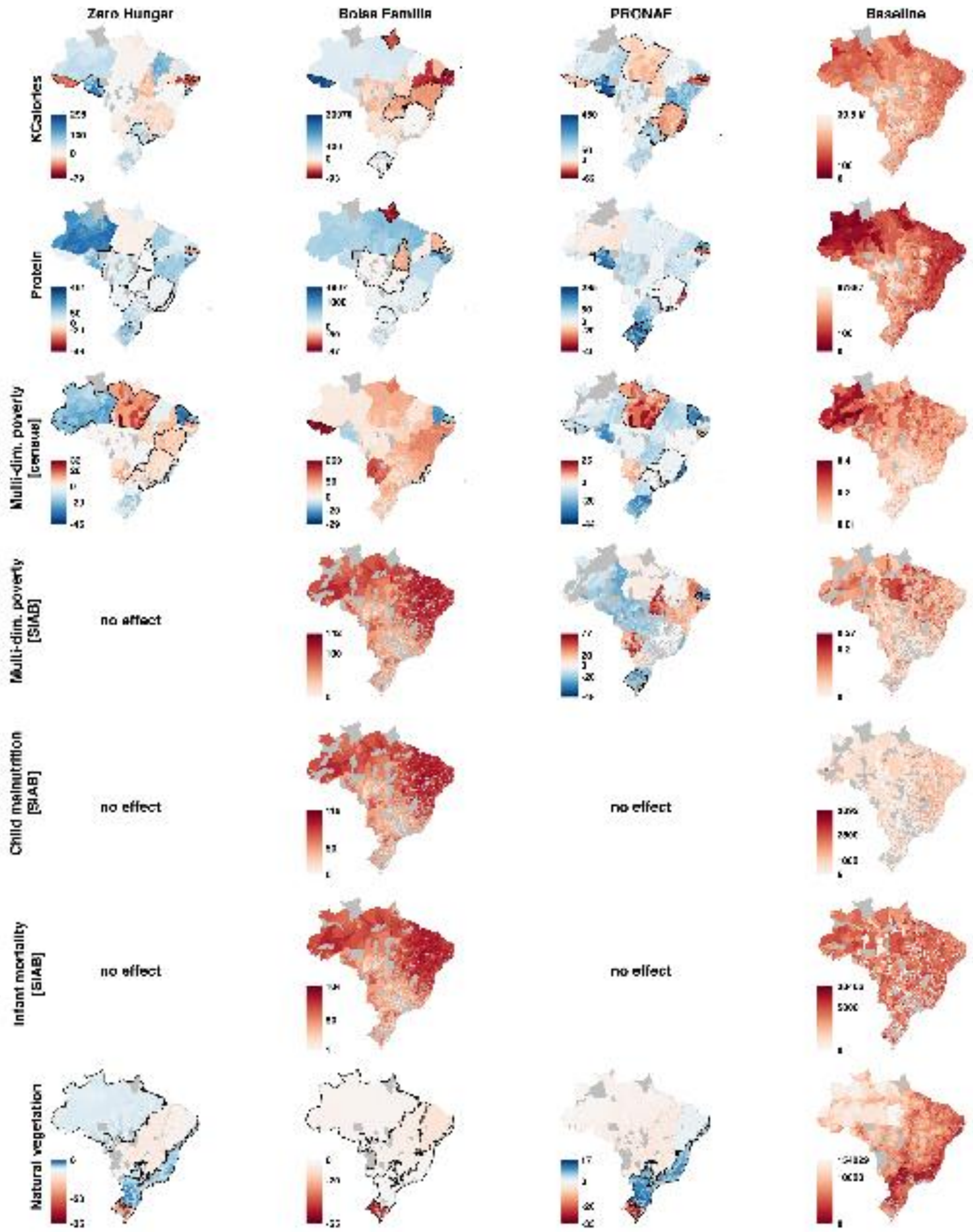

Fig. 1. Relative impact of Zero Hunger, Bolsa Familia and PRONAF investment (column 1-3) on daily per capita kilocalorie production, daily per capita protein production, multi-dimensional poverty in the entire population (census), multi-dimensional poverty in the poorer sectors of society (SIAB), child malnutrition in the poorer sectors of society (SIAB) and natural vegetation cover (km^2). Relative impact is defined as the modelled change (%) in the outcome variable when investment increases from a spatially uniform negligible value (1^{st} percentile value) to the actual investment level. Column 4 shows outcome values at baseline (i.e. year 2000 for multi-dimensional poverty (census) and 2004 for all others). 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 biome (in the natural vegetation cover model). 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, where in columns 1-3 blue indicates beneficial impacts and red non-beneficial impacts. In maps of baseline values (column 4) deeper red indicates municipalities with a worse starting condition, such as high multi-dimensional poverty or lower coverage of natural vegetation. Grey areas signify municipalities not included in the analysis because they were urban, have insufficient data or fall within the model reference state or biome for which no model statistics are available.

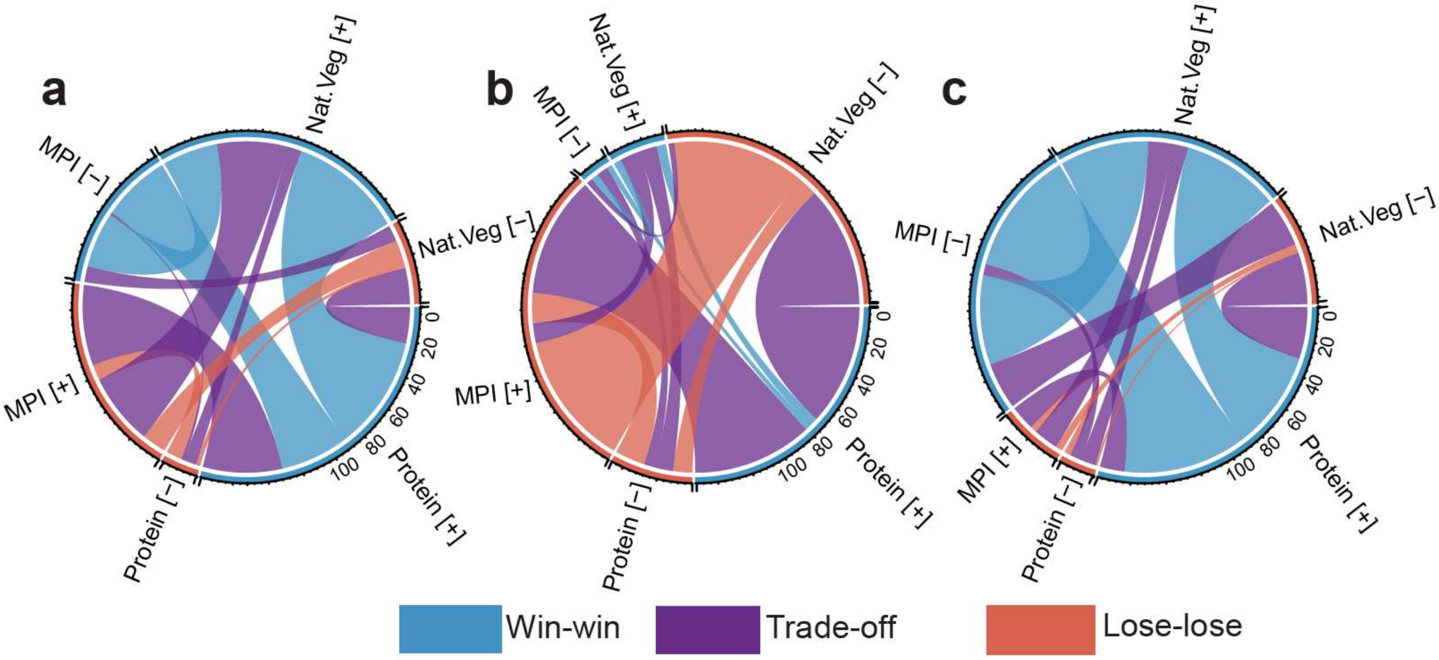

Fig. 2. Positive synergies (win-wins), trade-offs (win-lose) and negative synergies (lose-lose) from **a)** ZH, **b)** BF and **c)** PRONAF investment across three examples of sustainability outcomes, i.e. changes in per capita protein production (SDG 2), multi-dimensional poverty (census; SDG 1) and natural vegetation (SDGs 13 & 15). These have been selected as examples of key outcomes related to divergent SDGs. Coloured bands indicate the type of relationship (positive synergies (win-win), negative synergies (loose-loose) or trade-offs) between outcome variables; with the thickness of each link representing the percentage of municipalities that exhibit each type of relationship for each pair of outcome variables (indicated by the scale bar on the edge of each circle). Impact of program outcomes is calculated from robust multivariable regression models of a covariate-balanced sample (Table 1; n = 4,663-4,924 municipalities depending on the outcome pairings).

Supplementary Information for

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

Cecilie Dyngeland[1], Johan A Oldekop[2], Karl L Evans[1]

Author affiliations:

[1]Department of Animal and Plant Sciences, The University of Sheffield, Sheffield S10 2TN, UK

[2]Global Development Institute, The University of Manchester, Manchester M13 9PL, UK

Address correspondence to: [Cecilie Dyngeland, cecidy85@gmail.com]

Corresponding author:
Cecilie Dyngeland (cecidy85@gmail.com)

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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

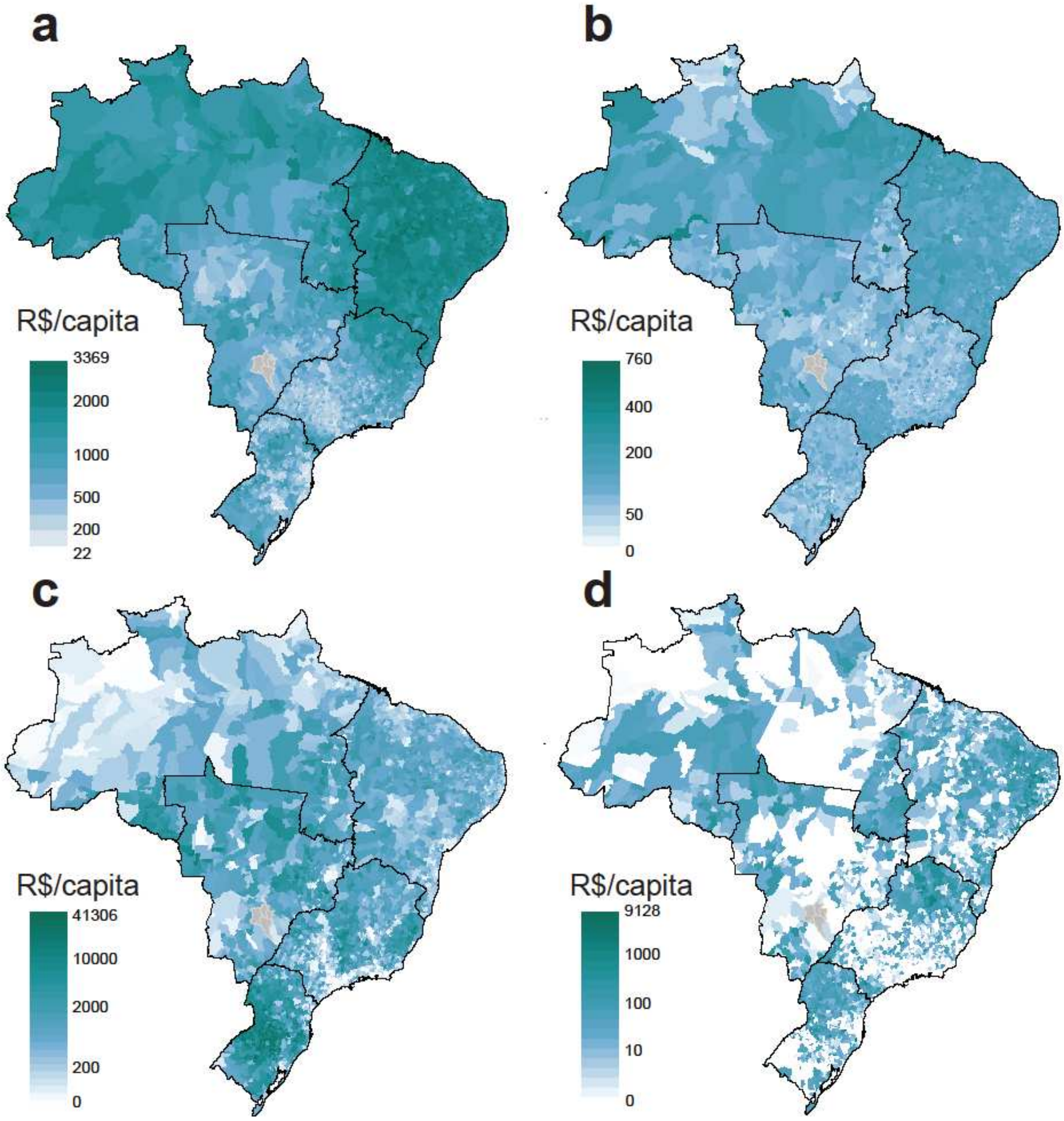

Fig. S1. Total investment per capita in Brazilian reals (R$) from 2004-2013 for the main Zero Hunger sub-programs **a** Bolsa Familia, **b** PNAE, **c** PRONAF and **d** PAA, available at www.dados.gov.br/www.mds.gov.br, showing great spatial variation in investment within and across programs. Grey areas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

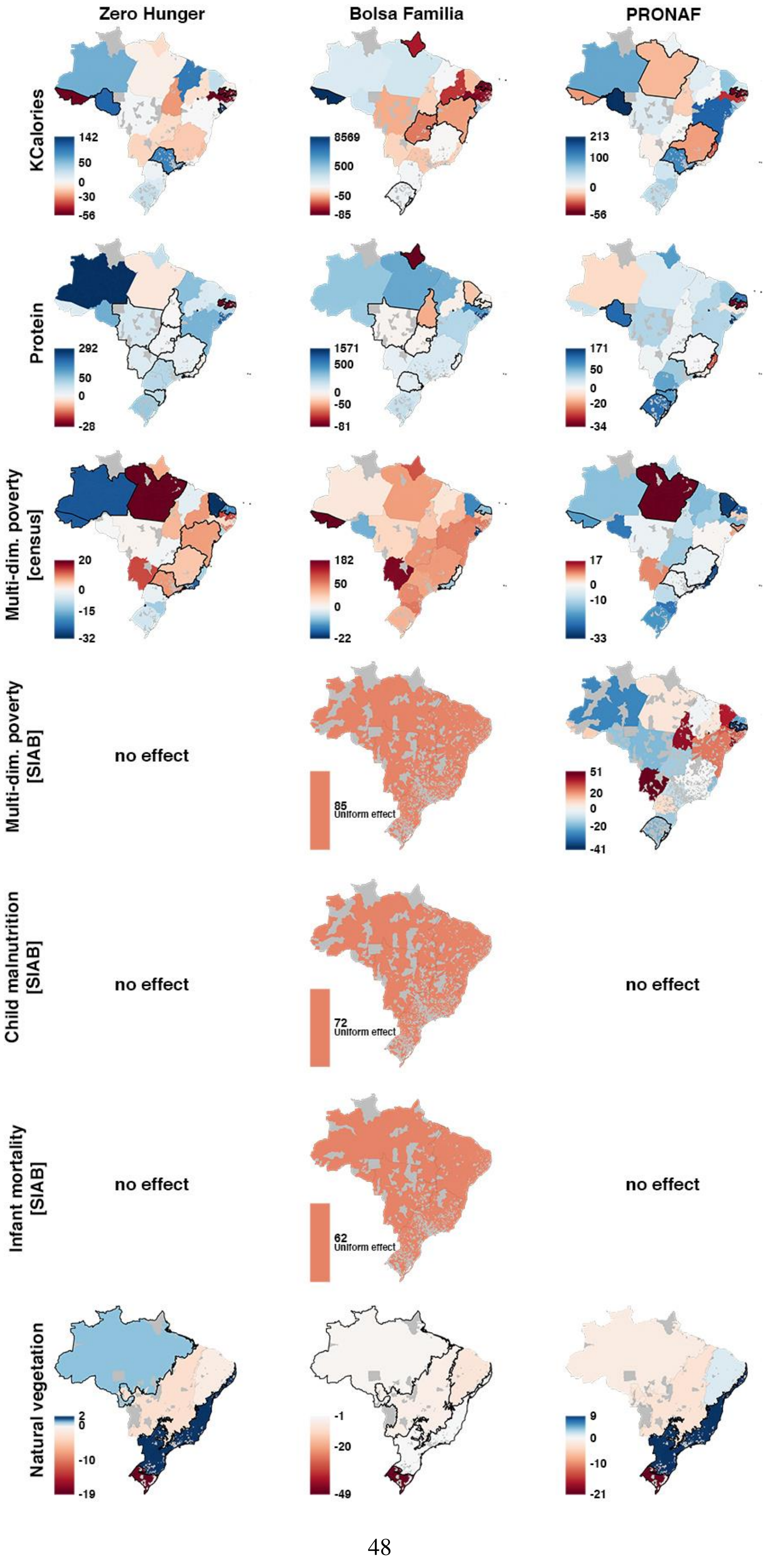
Zero Hunger
Bolsa Familia
PRONAF
KCalories
142
50
0
-30
-56
8569
500
-50
-85
213
100
0
-56
Protein
292
50
0
-28
1571
500
0
-50
-81
171
50
0
-20
-34
Multi-dim. poverty [census]
20
0
-15
-32
182
50
0
-22
17
0
-10
-33
Multi-dim. poverty [SIAB]
no effect
85
Uniform effect
51
20
0
-20
-41
Child malnutrition [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

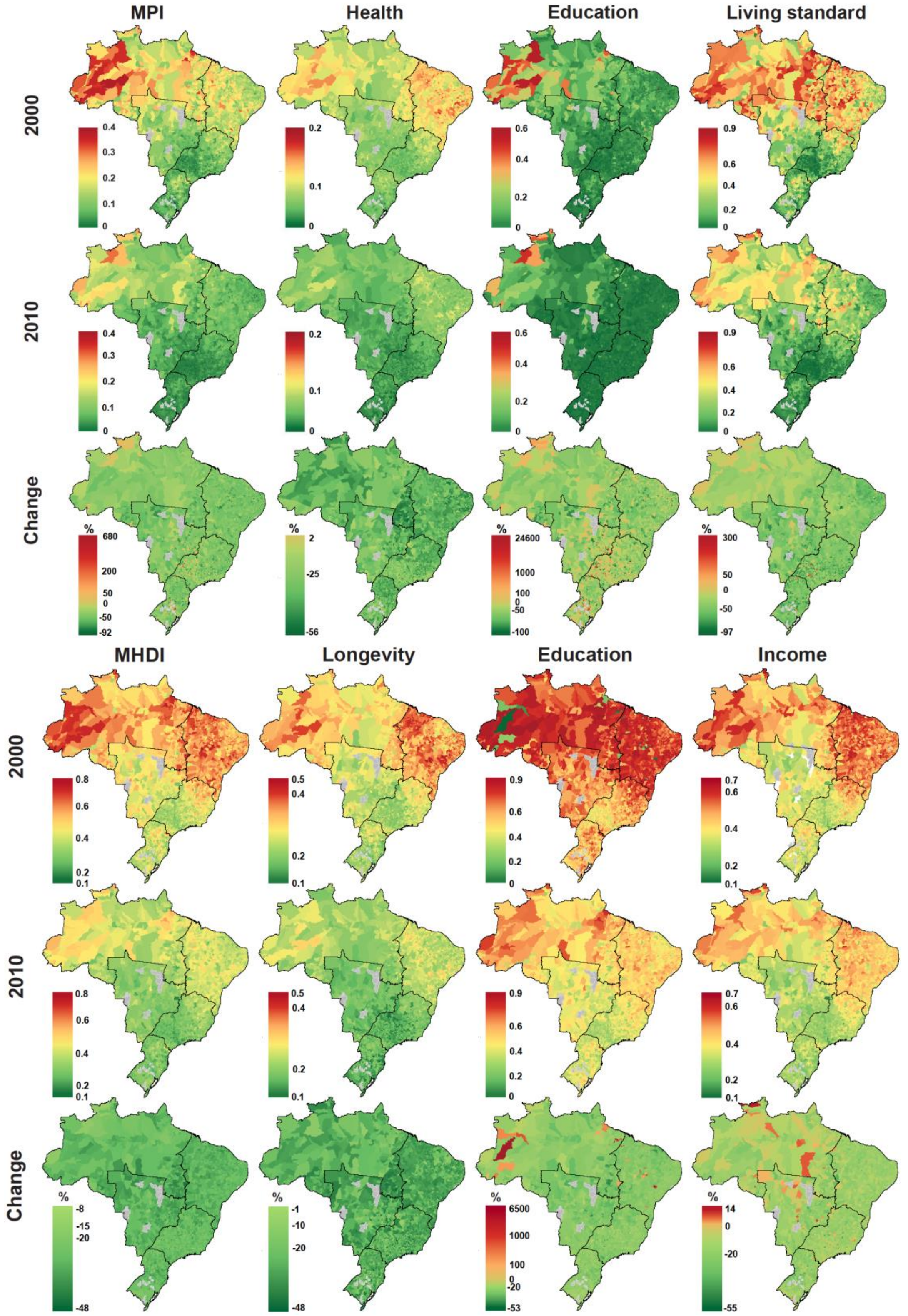

Fig. S3. High consistency between multi-dimensional poverty (census) (MPI) overall and its three dimensions Health, Education and Living Standard for 2000 and 2010 (top 3 rows), and the Brazilian Municipal Human Development Index (MHDI) (when negatively loaded) and its three dimensions Longevity, Education 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

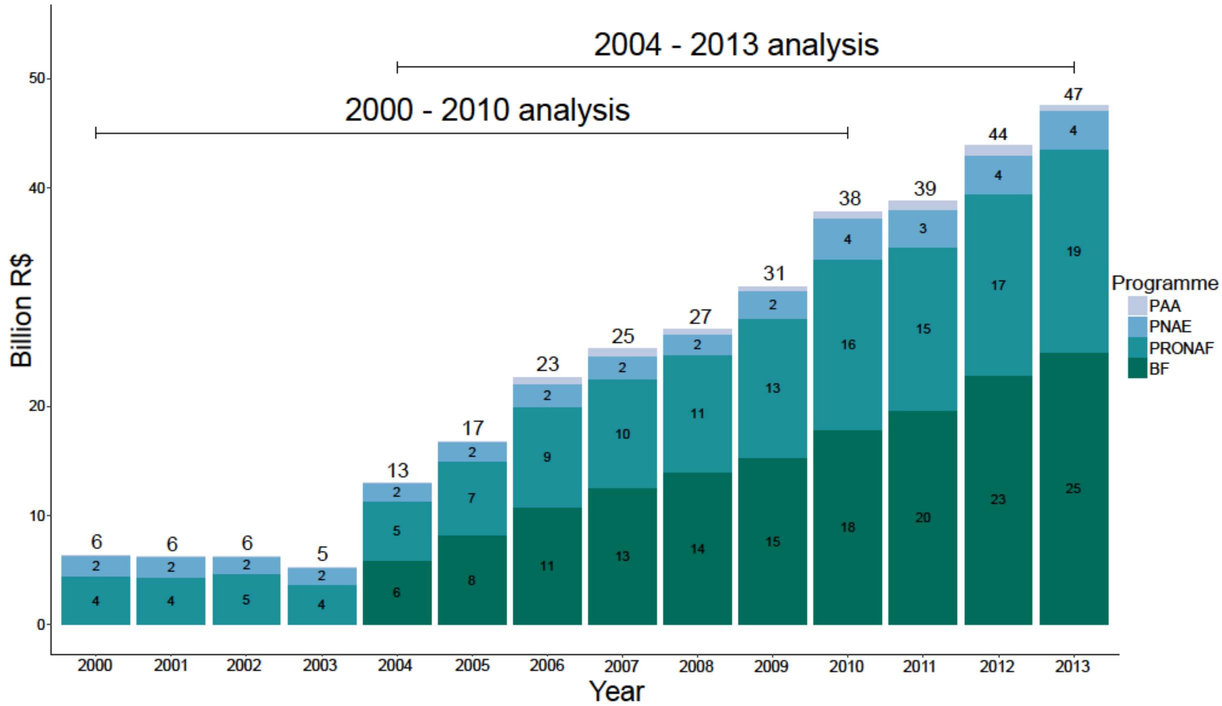

Fig. S4. Annual investments in the four main Zero Hunger (ZH) sub-programs Bolsa Familia (BF), PRONAF, PNAE and PAA available at www.dados.gov.br/www.mds.gov.br, showing a gradual increase in annual investments and predominance of BF and PRONAF to a summed ZH investment. Horizontal lines indicate investment 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

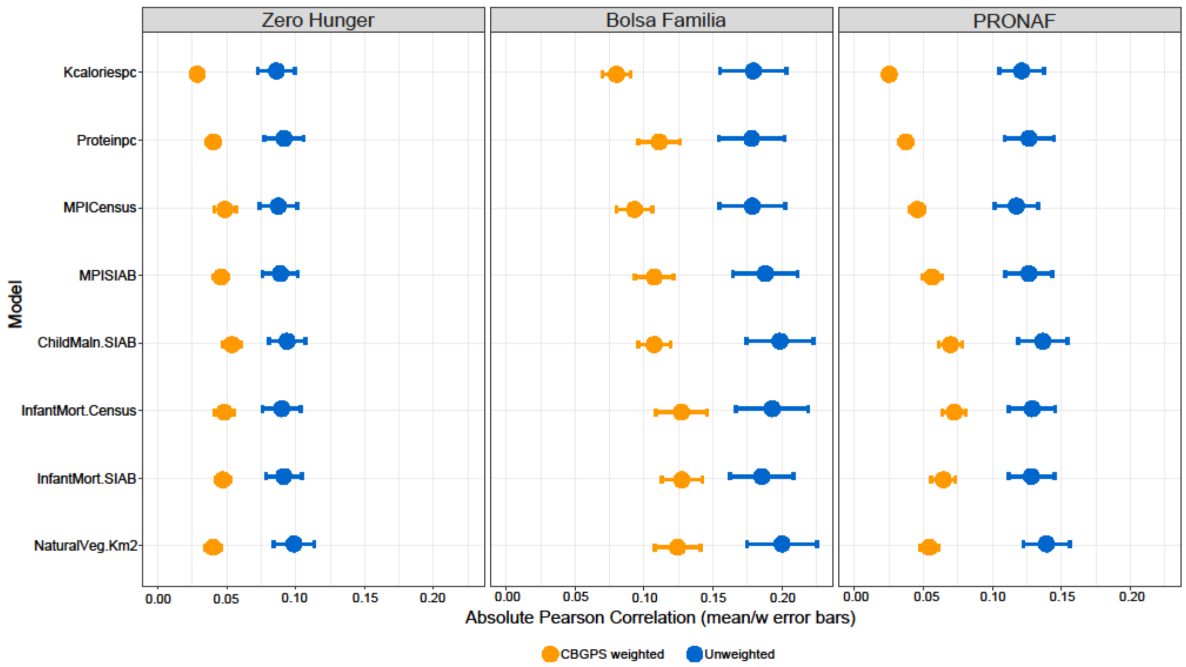

Fig. S5. Great covariate balance achieved following the Covariate balancing generalized propensity score (CBGPS) method from Fong et al. (50). Orange circles shows average absolute Pearson correlation between the Zero Hunger, Bolsa Familia and PRONAF investment variable and model covariates (predictor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

References.

1. E. J. de Mattos, I. P. Bagolin, Reducing Poverty and Food Insecurity in Rural Brazil: the Impact of the Zero Hunger Program. *EuroChoices* **16**, 43–49 (2017).
2. A. W. Kepple, A. Carolina, F. Silva, E. A. Fernandes, "The state of food and nutrition security in Brazil: A multi-dimensional portrait" (2014).
3. OECD, "OECD regional typology" (2011).
4. J. F. Rodrigues, O rural e o urbano no Brasil : uma proposta de metodologia de classificação dos municípios. *Anal. Soc.* **211**, 431–456 (2014).
5. R. Remans, S. a. Wood, N. Saha, T. L. Anderman, R. S. DeFries, Measuring nutritional diversity of national food supplies. *Glob. Food Sec.*, 1–9 (2014).
6. IBGE, Produção Agrícola Municipal (2016) (May 1, 2016).
7. FBA/USP, Tabela Brasileira de Composição de Alimentos: Brasilfoods (2008) (April 1, 2016).
8. USDA, USDA National Nutrient Database for Standard Reference, Release 21 (2008) (April 1, 2016).
9. J. G. da Silva, M. E. Del Grossi, C. G. de França, *The Fome Zero (Zero Hunger) Program: The brazilian experience*, J. G. da Silva, M. E. Del Grossi, C. G. de França, Eds. (2011).
10. S. Alkire, J. Foster, Counting and multidimensional poverty measurement. *J. Public Econ.* **95**, 476–487 (2011).
11. Atlas Brazil, The MHDI: Atlas of Human Development in Brazil (2013) (November 3, 2015).
12. Ministerio da Saude, SIAB: Sistema de Informação de Atenção Básica (2015) (March 18, 2015).
13. D. Rasella, R. Aquino, M. L. Barreto, Impact of the Family Health Program on the quality of vital information and reduction of child unattended deaths in Brazil: an ecological longitudinal study. *BMC Public Health* **10**, 380 (2010).
14. H. Young, S. Jaspars, "Review of Nutrition and Mortality Indicators for the Integrated Food Security Phase Review of Nutrition and Mortality Indicators for the IPC: Reference Levels and Decision-making" (2009).
15. A. C. Xavier, C. W. King, B. R. Scanlon, Daily gridded meteorological variables in Brazil (1980-2013). *Int. J. Climatol.* (2015) https:/doi.org/10.1002/joc.4518.
16. MapBiomas, Coleções MAPBIOMAS (2017) (August 20, 2017).
17. M. Junior, Governo gastou R$ 62 bilhões com Fome Zero desde 2003. *Contas Abertas* (2009).
18. A. Soares, F.V.Nehring, R.Schwengber, R.B.Rodrigues, C.G.Lambais, G.Balaban, D.S.Jones, C. , Galante, "Structured Demand and Smallholder Farmers in Brazil: the Case of PAA and PNAE" (2013).
19. L. Mourao, M. C. Ferreira, A. M. de Jesus, Evaluation of the Brazilian Family Grant Program : A Quasi-Experimental Study in the State of Rio de Janeiro. *Psicol. Reflex. e Crit.*, 719–729

(2009).

20. K. S. Andam, P. J. Ferraro, A. Pfaff, G. A. Sanchez-Azofeifa, J. A. Robalino, Measuring the effectiveness of protected area networks in reducing deforestation. *Proc. Natl. Acad. Sci.* **105**, 16089–16094 (2008).
21. C. van Stolk, S. Patil, What matters in the demand and supply of services in Bolsa Familia: a look at contextual factors that affect the quality of implementation in *Paper Prepared for the ECPR General Conference, Bordeaux, 4 – 7 September 2013*, (2013).
22. MMA, *Priority Areas for the Conservation , Sustainable Use and Benefit Sharing of Brazilian Biological Diversity* (Ministry of the Environment, 2007).
23. IBGE, MMA, Mapa de Biomas e de Vegetação (2004) (May 1, 2016).
24. World Bank, "World Development Report 2008: Agriculture for Development" (2008) https:/doi.org/10.1596/978-0-8213-7233-3.
25. IBGE, Produto Interno Bruto dos Municipios (2015) (June 22, 2015).
26. C. Zucco, When Payouts Pay Off: Conditional Cash Transfers and Voting Behavior in Brazil 2002–10. *Am. J. Pol. Sci.* **57**, 810–822 (2013).
27. C. Vergne, Democracy , Elections and Allocation of Public Expenditure in Developing Countries. *halshs-00564572* (2011).
28. M. Elinder, H. Jordahl, P. Poutvaara, Promises , policies and pocketbook voting. *Eur. Econ. Rev.* **75**, 177–194 (2015).
29. M. T. S. Arretche, *Estado Federativo e Políticas Sociais: Determinantes da Descentralização* (Revan, 2000).
30. Tribunal Superior Eleitoral, Repositório de dados eleitorais (2020) (March 2, 2020).
31. IBGE, Censo Agropecuário (Agricultural census) (2006) (November 25, 2014).
32. J. a Berdegué, R. Fuentealba, Latin America: The state of smallholders in agriculture. *Pap. Present. IFAD Conf. New Dir. Smallhold. Agric.* **Session 3** (2011).
33. JRC Science Hub, Global Environmental Monitoring - Map showing the travel time to major cities - JRC Science Hub - European Commission (2014) (October 9, 2015).
34. European Space Agency, ESA CCI Land cover (2014) (October 9, 2015).
35. FGM, IBGE: versão atualizada da Base Cartográfica Contínua do Brasil está disponível (2013) (May 1, 2016).
36. Aster GDEM, ASTER GDEM (2011) (October 9, 2015).
37. J. A. Oldekop, K. R. E. Sims, M. J. Whittingham, A. Agrawal, An upside to globalization : International outmigration drives reforestation in Nepal. *Glob. Environ. Chang.* **52**, 66–74 (2018).
38. G. Guedes, S. Costa, E. Brondizio, Revisiting the hierarchy of urban areas in the Brazilian Amazon: a multilevel approach. *Changes* **29**, 997–1003 (2012).
39. M. R. Moreira, S. Escorel, Municipal Health Councils of Brazil: a debate on the

democratization of health in the twenty years of the UHS. *Cien. Saude Colet.* **14**, 795–806 (2009).

40. R. Glickhouse, Brazil Update: Historic Drought Takes Toll on Agriculture (2015) (August 25, 2015).
41. C. Stauffer, Worst drought in decades hits Brazil's Northeast (2013) (August 25, 2015).
42. D. Sietz, *et al.*, Smallholder agriculture in Northeast Brazil: Assessing heterogeneous human-environmental dynamics. *Reg. Environ. Chang.* **6**, 132–146 (2006).
43. S. Beguería, S. M. Vicente Serrano, SPEIbase v.2.3 (2014) (August 25, 2015).
44. Banco Central do Brasil, Crèdito Rural (2017) (August 31, 2017).
45. M. R. Rosenzweig, K. I. Wolpin, Credit Market Constraints , Consumption Smoothing , and the Accumulation of Durable Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries : Investments in Bullocks in India. *J. Polit. Econ.* **101**, 223–244 (1993).
46. R. Burgess, R. Pande, Do rural banks matter? Evidence from the Indian social banking experiment. *Am. Econ. Rev.* **95**, 780–795 (2005).
47. J. Assunção, C. Gandour, R. Rocha, R. Rocha, "The Effect of Rural Credit on Deforestation : Evidence from the Brazilian Amazon" (2016).
48. G. Fischer, H. Van Velthuizen, M. Shah, F. Nachtergaele, *Global Agro-ecological Assessment for Agriculture in the 21st Century : Methodology and Results* (2002).
49. B. Soares-Filho, *et al.*, Role of Brazilian Amazon protected areas in climate change mitigation. *Proc. Natl. Acad. Sci.* **107**, 10821–10826 (2010).
50. C. Fong, C. Hazlett, K. Imai, Covariate Balancing Propensity Score for a Continuous Treatment : Application to the Efficacy of Political. *Forthcom. Ann. Appl. Stat.* (2017).
51. E. A. Stuart, D. B. Rubin, "Best practices in quasi-experimental designs: Matching methods for causal inference" in (2007), pp. 155–176.
52. M.-L. Delignette-Muller, C. Dutang, R. Pouillot, J.-B. Denis, A. Siberchicot, Package ' fitdistrplus .' *Compr. R Arch. Netw.* (2019).
53. P. Rousseeuw, *et al.*, Package 'robustbase.' *Compr. R Arch. Netw.* (2015).
54. C. Croux, G. Dhaene, D. Hoorelbeke, "Robust standard errors for robust regression estimators" (2003).
55. C. Kleiber, A. Zeileis, Package ' AER .' *Compr. R Arch. Netw.* (2019).
56. J. M. Ver Hoef, P. L. Boveng, Quasi-Poisson vs . Negative Binomial Regression : How Should We Model Overdispersed Count Data: *Ecology* **88**, 2766–2772 (2007).
57. S. Coxe, S. G. West, L. S. Aiken, The Analysis of Count Data : A Gentle Introduction to Poisson Regression and Its Alternatives. *J. Pers. Assess.* **91**, 121–136 (2009).
58. D. A. Belsley, E. Kuh, R. E. Welsch, *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity* (John Wiley & Sons, 2005).

59. M. H. Kutner, C. J. Nachtsheim, J. Neter, W. Li, *Applied Linear Statistical Models*, Fifth Edit (McGraw-Hill/Irwin, 2005).
60. S. Guo, M. W. Fraser, "Counterfactual Framework and Assumptions" in *Propensity Score Analysis: Statistical Methods and Applications*, (SAGE Publications Ltd, 2015), p. 448.
61. C. J. Paciorek, The Importance of Scale for Spatial-Confounding Bias and Precision of Spatial Regression Estimators. *Stat. Sci.* **25**, 107–125 (2010).
62. D. I. Gregorio, L. M. DeChello, H. Samociuk, M. Kulldorff, Lumping or splitting: seeking the preferred areal unit for health geography studies. *Int. J. Health Geogr.* **4**, 6 (2005).
63. Ministerio da Saude, "Sistema de Informação da Atenção Básica SIAB Indicadores 2002" (2003).
64. P. Legendre, Spatial Autocorrelation : Trouble or New Paradigm? *Ecology* **74**, 1659–1673 (1993).
65. M. Altman, *et al.*, *Package "spdep"* (2019) https:/doi.org/10.1016/j.csda.2008.07.021.
66. J. A. Oldekop, K. R. E. Sims, B. K. Karna, M. J. Whittingham, A. Agrawal, Reductions in deforestation and poverty from decentralized forest management in Nepal. *Nat. Sustain.* **2**, 421–428 (2019).
67. I. Nunes, *et al.*, Animal Performance and Carcass Characteristics of Bulls (1/2 Purunã vs 1/2 Canchim) Slaughtered at 16 and 22 Months Old , and Three Different Weights. *Asian Australas. J. Anim. Sci.* **28**, 612–619 (2015).
68. M. R. S. Peixoto, *et al.*, Carcass quality of buffalo (Bubalus bubalis) finished in silvopastoral system in the Eastern Amazon, Brazil. *Arq. Bras. Med. Veterinária e Zootec.* **64**, 1045–1052 (2012).
69. P. Faria, *et al.*, Carcass and parts yield of broilers reared under a semi-extensive system. *Rev. Bras. Ciência Avícola* **12**, 153–159 (2010).
70. M. T. M. Cardoso, A. V. Landim, H. Louvandini, C. McManus, Performance and carcass quality in three genetic groups of sheep in Brazil. *Rev. Bras. Zootec.* **42**, 734–742 (2013).
71. R. Maria, B. Lima, W. H. De Sousa, A. N. De Medeiros, G. R. De Medeiros, Revista Brasileira de Zootecnia Characteristics of the carcass of goats of different genotypes fed pineapple (Ananas comosus L .) stubble hay. **44**, 44–51 (2015).
72. T. M. Bertol, *et al.*, Effects of genotype and dietary oil supplementation on performance, carcass traits, pork quality and fatty acid composition of backfat and intramuscular fat. *Meat Sci.* **93**, 507–16 (2013).
73. IBGE, Censo Demografico (2010) (March 27, 2018).
74. U. MMA, Embrapa, Inpe, Ibama, UFG, Mapeamento do Uso e Cobertura da Terra do Cerrado: Projeto TerraClass Cerrado 2013 (2015).