The Impact of Social and Environmental protection programmes on food security and the environment

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Abstract

Social and environmental protection programmes are common strategies to deliver improvements in social and environmental conditions. Holistic analysis of interventions which examine linkages between multiple sustainable development outcomes are key for understanding transitions to sustainability and make progress towards sustainable development. This thesis uses a multidisciplinary approach and focuses on Brazils' flagship Zero Hunger social protection programme and the National Rural Environmental Registry (CAR), and the role of small-scale farmers, to examine intended and unintended outcomes and trade-offs of the interventions. Specific outcomes of focus are multi-dimensional poverty, food insecurity and health, use of agro-chemical (inorganic fertilizer and pesticide), expansion of agricultural area (crop and pasture) and and natural vegetation loss. Results show that social and environmental protection programmes which focuses on small-scale farmers can deliver simultaneous beneficial social and environmental outcomes. However, trade-offs and heterogeneous effects often occur. These heterogeneities arise for three primary reasons. First, programme impacts vary across food security, multi-dimensional poverty, health and environmental outcomes, with evidence for positive, negligible and negative impacts depending on the outcome in question. Second, within a single outcome impacts vary depending on the specific programme activities, in particular whether support to small-scale farmers is given through conditional cash transfers, agricultural credit, support for agricultural market access or environmental monitoring. Third and finally, within a single outcome and specific programme activity there is considerable variation in the magnitude and even direction of impact. This variation in impact we find both spatially across Brazil and across the types of farmers that participate. These differences in impact is driven primarily by variation in local contexts and variation in characteristics of programme participants. The success of the Zero Hunger and CAR programmes, and likely the success of integrated social and environmental programmes in other developing countries, have been identified to rely on three main conditions: the presence of basic infrastructure, the presence and collaboration of institutions across sectors, and appropriate programme design and targeting to engage the poorest and most in need farmers.

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- Chapter 2 has been written with the aim of publication in Proceedings of the National Academy of Sciences of the USA as:

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Chapter 2 was the result of a collaborative effort from CD, JAO and KLE. JAO and KLE conceived the original idea and concept. CD, JAO and KLE designed the methodology. CD gathered the data, performed the analysis and drafted the initial manuscript. JAO and KLE revised the manuscript and provided important theoretical and intellectual input.

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Chapter 4 was the result of a collaborative effort. SJ and LVR conceived the original idea and concept. Design of study was made jointly by SJ, CD, and LVR. LR provided CAR data, SJ price and precipitation data and CD all additional data. SJ and CD performed the analysis, interpreted the results and drafted the initial manuscript. LR and LVR revised the manuscript and provided important theoretical and intellectual input.

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Chapter 1

1. Thesis Introduction

"Hunger is on the rise". Those were the opening words from FAO when it released the newest report on the state of food security and nutrition in the world (FAO, 2018). Increasing for the third year in a row the absolute number of undernourished people reached nearly 821 million in 2017, returning us to global hunger levels from almost a decade ago (Ibid). At the same time agriculture continues to be a main driver of natural vegetation and biodiversity loss and greenhouse gas emissions (Newbold et al., 2015; Tubiello et al., 2015). Ironically, these environmental changes are likely to have negative knock-on effects on future agricultural production at both local and regional scales. For instance, the conversion of Amazon forest to pasture and arable land has not only negatively impacted biodiversity and carbon storage but associated loss of natural resources has driven long-term declines in local livelihoods (Rodrigues et al., 2009). In addition, it has disrupted the water cycle and increased the occurrence and severity of droughts in the Amazon and elsewhere (Nazareno & Laurance, 2015), leading to adverse impacts on agricultural yields (Mercure et al., 2019).

It is increasingly recognized that food security is about more than food production, in fact, sufficient food is produced globally to feed the entire global population (Meyfroidt, 2018). Food security is commonly defined to exist "when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (CFS, 2012). To achieve food security thus requires multiple food system components to be met simultaneously, and besides food production, it also incorporates issues such as poverty and health. Food security, poverty alleviation, health and environmental protection are all major global challenges in their own right and are commonly reflected in national development plans and international sustainability agendas, including the current Sustainable Development Goals (SDGs).

In addition, smallholder farmers are increasingly identified as vital for achieving the multiple SDGs of food security, poverty alleviation, protection of biodiversity and natural resources (Samberg et al., 2016; UNCTAD, 2015). There is estimated to be more than 500 million small farms world-wide (Lowder et al., 2016). Small-scale farmers often experience high levels of food insecurity and poverty (UNCTAD, 2015). At the same time, they make significant contributions to both domestic and global food supply (Samberg et al., 2016) and contrary to traditional beliefs, small-scale farms have been shown able to offer higher productivity than larger-scale farmers (Tscharntke et al., 2012). Moreover, small scale farmers frequently have reduced negative environmental impacts compared to larger scale mono crop farmers as they tend to use less chemical inputs (Altieri et al., 2011) and adopt more diversified production systems which benefit biodiversity and provides important connecting points between native vegetation fragments (Perfecto et al., 2009; Perfecto & Vandermeer, 2010). This is important given that long-term sustainability of food production is facilitated by healthy and biologically diverse environments that provide the ecosystem services needed for production (Liao & Brown, 2018).

Consequently, policies that aim to support small-scale farmers may facilitate progress towards food security whilst also support the additional SDG ambitions of ending poverty and ensuring environmental sustainability. It is important to keep in mind, however, that heterogeneity exists also within small-scale farmers, and there is no clear-cut distinction between smallholders and large-scaled farming (though in literature it often is framed as such (Meyfroidt, 2018). Small-scale farms are often defined as farms of less than 2 hectare (Lowder et al., 2016), though other thresholds range from 5 hectare, and some countries can even consider farm size up to 100 hectare as more similar of small-scale farming than large-scale (Berdegué & Fuentealba, 2011; Samberg et al., 2016). This variation is driven mainly by regional variation. For instance, while a 2 ha threshold might be fitting for many smallholder farmers in Asia and Africa (Lowder et al., 2016), it is not for the majority of smallholders in Latin America and the Caribbean where farm sizes tend to be larger (Berdegué & Fuentealba, 2011). Another common characteristic of small-scale farmers is the use of family labour and the family unit as manager of the farm. Due to this, the terms smallholder and family farms are often used interchangeably (Lowder et al., 2016). Meyfroidt also highlights the emergence of (what he calls) medium scale farmers, i.e. farmers which are more commercial-oriented and larger than the typical smallholder farmer, generally of sizes between 5 and 100 hectare, that are smaller than the typical capitalized large-scale farms. Such farms can for instance be smallholders who have consolidated land by acquiring nearby plots, or urban inhabitants acquiring farmland in the countryside (Meyfroidt, 2018). Importantly, this set of farmers might still be characterized, and thus eligible for interventions aimed at small-scale or family farmers (Berdegué & Fuentealba, 2011). According to Meyfroidt, this group of farmers might utilize investments more effectively than the smallest farmers, and could be particularly important for poverty alleviation as they can both increase food production (thus improving their own livelihoods) and generate farm labour (thus providing income opportunities for smaller-scale farmers) (Meyfroidt, 2018).

In addition to the size of the farm, the impact of investment in agriculture might also vary depending on the farm type and commodity it targets. For instance, investments in land use intensification through agro forestry and agroecology schemes are argued by some authors to not only mitigate agricultural and environmental trade-offs, but to be more beneficial for local food insecure populations (Fischer et al., 2017); while intensification of staple crop production is often vital for poor subsistence farmers which are disconnected from markets and off-farm opportunities to reduce food insecurity (Jayne et al., 2014). Increasing productivity on existing land, particularly for crops with inelastic demand such as staple crops in closed (local or national) markets might also spare land for conservation (Meyfroidt, 2018). However, intensification can also lead to a rebound effect, i.e. further expansion of farmland (at the expense of natural vegetation) as production becomes more profitable. This latter scenario if often found for globally traded products with high demand such as meat, feed and energy crops (e.g. soy or palm oil) (Ibid.). Small-scale farmers, though, are often found to be hindered from participating in such markets (particularly due to farm capacity limitations) and will not benefit from such interventions directly, and if at all that would be through the trickle down effects on the labour market as described by Meyfroidt (Meyfroidt, 2018). To minimize such an adverse trade-off with the environment, many authors call for agricultural investments to be accompanied by or linked up with existing interventions which aim to limit land use expansion, for instance by introducing land zoning (Bruggeman et al., 2015), supply chain interventions for main commodity crops (J. Alix-Garcia & Gibbs, 2017) or restrictions on agricultural credit based on deforestation history (Assunção et al., 2016).

It is thus evident that a holistic approach to food security, poverty alleviation, human health and environmental conservation is needed in order to capture multiple interactions and trade-offs between social and environmental aspects. Unfortunately, cross-sectorial collaboration tend to be the exception rather than the rule (Sayer et al., 2013) and interventions (and evaluations) aimed to tackle societal and environmental problems tend to focus only on single issues (Oldekop et al., 2019). This means that trade-offs are often overlooked, and we run the risk of making incomplete and wrong conclusions when evaluating specific interventions (Coates, 2013; Liao & Brown, 2018). This issue is becoming increasingly recognized, and calls for more holistic approaches have arisen from multiple fields, e.g. agricultural production (Liao & Brown, 2018), food security (Ingram, 2011), environmental conservation (Sayer et al., 2013) and the SDGs (Barbier & Burgess, 2017).

There is increasingly a definite sense of urgency felt in scholarly work and policy discussions focused on sustainability issues (Chappell & LaValle, 2011) and numerous publications now refer to what is described as the future "perfect storm" of events, i.e. a time when we will face the challenge to feed a growing population on diminishing supplies of land, water and energy (Beddington, 2009). As such it is vital for us to understand now, which interventions have been effective and which have not, and why both from an environmental and societal point of view. This dissertation attempts to do just that. Specifically, it asks (1) are there interventions for small-scale farmers that simultaneously meet health, poverty, food and environmental outcomes? In addition, it asks (2) are there interventions that involve small-scale farmers that tackle the environment without trade-offs with other societal outcomes?

As previously described, small-scale farmers play a potentially vital role in achieving multiple sustainability outcomes. Therefore I have selected them as a target population when considering appropriate interventions to focus on. Some types of agricultural interventions, such as improved agricultural technologies or investment in rural infrastructure, can be scale neutral and benefit small- and large-scale farmers alike (Gollin, 2014). However, agricultural interventions has tended to favour larger farms by providing them with subsidized credit, infrastructure provision (in areas dominated by large farms) or guaranteed commodity crop prices (Poulton et al., 2010). In addition, although well-conducted agricultural interventions likely increase productivity and food availability (Webb &

Kennedy, 2014) this does not automatically lead to improvements in other livelihood outcomes. For instance, there is inconclusive evidence regarding whether increased food production also leads to nutrition improvements (Webb & Kennedy, 2014), and some authors suggest that additional investments in other capital such as human capital (e.g. education) are needed for such dual outcomes to materialize (Berti et al., 2003).

Because small-scale farmers suffer from a whole range of challenges (e.g. land inequality and unequal access to input and output markets, financial services and technical advice), Hazell et al. (2007) highlight that for interventions to benefit small-scale farmer livelihoods these must aim at reducing the biases against small-scale farmers and get the basics in place (Hazell et al., 2007). In fact, interventions aimed specifically at small-scale farmers often fall within broader policy debates of rural poverty, and in many regions improving small-scale farmer livelihoods is viewed best addressed through social protection programmes, food assistance or input subsidy programmes (Jayne et al., 2014). According to Barrientos (2017), antipoverty interventions in rural areas (where the majority of small-scale farmers reside) can broadly be divided into three types based on their underlying understanding of poverty: pure income transfers; income transfers combined with asset accumulation; and integrated poverty reduction programmes (Barrientos 2017).

The first type, pure income transfers (sometimes also referred to as unconditional cash-transfers), target particularly vulnerable individuals or households such as households in extreme poverty, older people and people with disabilities. The underlying understanding of poverty for such programmes is that poverty is due to a mere deficit in income or consumption (which the transfer subsequently is expected to remedy) (Barrientos, 2017). Small-scale farmers often face liquidity constraints (Devereux et al., 2008) which can hinder their optimal allocation of productive resources. Subsequently, with the transfers, these households can purchase seeds, fertilizer or hire equipment and labour; as found to be the case for social pensioners in Bolivia (Barrientos, 2017). Pure income transfers do not challenge exclusion (social, economic and/or political) or structural biases against smallholders which are keeping these people in poverty. Such transfers are becoming increasingly common in Africa (Devereux, 2016). In addition, the level of the transfers are often too small to generate the desired outcome of poverty alleviation (Barrientos, 2017), and/or often fails to address inflation and food price seasonality (Devereux, 2016).

The second type, income transfers combined with asset accumulation, combines cash or kind transfers with accumulation of productive assets (e.g. human, physical or financial assets), in order to strengthen the productive capacity of poor households. As such, the underlying understanding of poverty is that it is due to deficits in both income and productive assets. According to Barrientos (2017), although these programmes adopt a multidimensional understanding of poverty, they tend to focus on just a few dimensions. They are very common in Latin-America and the Carribean (Cecchini & Madriaga, 2011). Here a series of countries have introduced programmes which transfer direct cash or in kind transfers (such as food supplements) conditioned on household participation in education and health, thus also commonly known as conditional cash-transfer programmes (Cecchini & Madriaga, 2011). Examples include Mexico's Oportunidades and Brazil's Bolsa Familia programme. The latter is the largest cash transfer programme in the world (Piperata et al., 2016) and has inspired the diffusion of conditional cash transfer programmes in both Latin-America and Sub-Saharan Africa (Leite et al., 2013). In both Oportunidades and Bolsa Familia cash is transferred to poor households conditioned on child school attendance and mother and child health check-ups (Piperata et al., 2016; Winters & Davis, 2009). Barrientos argues that these (human development) conditional cash transfer programmes can be particularly appropriate in rural areas because there generally is low baseline access to basic services. However, he also highlights the need for programme capacity to monitor the (compliance with) conditionalities and the fact that in many rural areas (particularly in Sub-Saharan Africa) there is limited availability of education and health infrastructure, which ultimately would hinder the expected benefits to materialize (Barrientos, 2017).

Other income transfers are rather combined with physical asset accumulation. These are often known as public works, cash/food for work, or guaranteed employment programmes. Examples include for instance the National Rural Employment Guarantee Scheme in India and the Productive Safety Net Programme in Ethiopia. A guarantee of employment is particularly relevant in areas where market employment is seasonal and variables (such as in rural agricultural communities) as it can stabilize income and livelihood well-being throughout the year, and reduce asset depletion caused by large fluctuations in seasonal income (Barrientos, 2017). In addition, as the employment is for productive work and focused for instance on creating permanent assets relevant for agriculture, such as irrigation facilities, flood control and roads (Basu, 2013); this should benefit the wider farm community. The ability of these programmes to deliver on multiple outcomes is found to be mixed (Barrientos, 2012). Many of these programmes transfer only a fraction of their budget to beneficiary households, and in some cases the value of the newly created infrastructure has been found to be marginal (Ibid.). In general, the success of these programmes are found to depend heavily on programme design (Ibid.) and local politics (Barrientos, 2017).

The third type, integrated poverty reduction programmes, combines a range of interventions focused on the poorest in order to remove wellbeing deficits and different forms of exclusion. Here poverty is also understood as multidimensional, but because poverty is rather understood to occur as a result of social, economic and/or political exclusion, it tends to cover a wider set of dimensions than the income transfers combined with asset accumulation (Barrientos, 2017). Through intermediaries such as social workers these programmes aim to connect poor households with public agencies to ensure a coordinated and comprehensive response by public agencies to remove sources of exclusion. For poor households in rural communities, gaining access to public agencies is particularly necessary as they often suffer from "fragmented and isolated responses by public agencies" despite being in great need of their support (Barrientos, 2017, p.107). As Hazell et al. highlighted, small-scale farmers in particular face a range of exclusions (Hazell et al., 2007), thus integrated poverty reduction programmes that focus on this sub-population could likely serve as an ideal case study of an intervention able to deliver on multiple social (and possibly environmental) outcomes. Examples of such integrated programmes include Challenging the Frontiers of Poverty Reduction – Targeting the Ultra Poor, in Bangladesh and the Minimum Living Standards Scheme in South Korea (Barrientos, 2017), and the Zero Hunger programme in Brazil (Silva et al., 2011). The latter programme focuses extensively on supporting (small-scale) family farmers and it is a well-known programme in international development discussions (FAO, 2014). In fact, the Zero Hunger programme is considered to be the primary mechanism through which Brazil met the Millennium Development Goal of halving extreme poverty and hunger by 2015 (Castaneda, 2012), and subsequently has spurred the diffusion of similar programmes throughout the developing world, particularly in Latin America and Africa (Fraundorfer, 2013; Milhorance et al., 2015). A holistic (systems approach) analysis into the social and environmental effects of the Zero Hunger programme could thus inform national development debates as well as international discussions.

Four sub-programmes are at the forefront of Zero Hunger: i) *The National Program to Strengthen Family Farming* (PRONAF) which provides small family run farms with low interest agricultural credits; ii) *The Food Acquisition Programme* (PAA) which provides these farms with access to price-controlled markets; iii) *The National School Feeding Programme* (PNAE) which provides free school meals to all children, and: iv) *The Bolsa Familia* sub-programme, which provides cash-transfers to poor households conditional on child school attendance and participation in family health check-ups and vaccination programmes (Silva et al., 2011) . Existing evaluations suggest Zero Hunger and its main sub-programmes are able to deliver beneficial health, poverty and food outcomes, e.g. Zero Hunger has been associated with increased farm incomes (Doretto & Michellon, 2007), increased food purchases in food insecure households (Agência IBASE, 2008), reduced child malnutrition (Paes-Sousa et al., 2011), and lower infant mortality (Rasella et. al, 2013). However, some evidence oppositely suggest negligible and at times negative effects on food production (J. a. Oldekop et al., 2015; Piperata et al., 2016; Thorkildsen, 2014), health and food security (Piperata et al., 2016; Soares et al., 2010). Only limited and mixed evidence exists regarding Zero Hungers' likely environmental impact. This includes mixed results on the impact on agro-chemical use (Chmielewska et al., 2010; Cunha et al., 2017; Mesquita & Bursztyn, 2017; Wittman & Blesh, 2017) and a positive effect on natural vegetation (though this study is only carried out in one community) (Thorkildsen, 2014). All these evaluations are limited, however, by a limited temporal, spatial or thematic focus and/or failure to consider spatial heterogeneities and key confounding factors.

The Zero Hunger programme is thus, an appropriate programme to focus on when attempting to answer whether there are interventions targeted at small-scale farmers which simultaneously meet health, poverty, food and environmental outcomes. The programme constitutes a major focus of this thesis. The programme is clearly primarily a social programme and although improving environmental conditions do also feature to some extent, e.g. PAA's support for agro-ecological food production

(Wittman & Blesh, 2017), this appears primarily to improve human conditions. Thus, in order to answer the second research question on whether interventions which are primarily focused on environmental aspects are able to do so without trade-offs with other (societal) outcomes, I focus on another Brazilian intervention, namely the national rural environmental registry (CAR) programme. The CAR programme geo-references and identifies property boundaries, Legal Reserves, and Areas of Permanent Preservation with the explicit aim of decreasing deforestation and environmental degradation by facilitating monitoring and enforcement (Azevedo et al., 2017). It is a mandatory legal tool and states that all rural properties including small-scale farm properties need to register. In addition, the CAR is linked to various institutional mechanisms, such a main commodity markets and rural credit, where access now depends on CAR registration and proven environmental compliance (Alix-Garcia & Gibbs, 2017; Assunção et al., 2016). As such, this programme is likely to influence small-scale farm livelihoods. Thus far, evaluations have focused primarily on its effect on deforestation and show significant and/or heterogeneous impacts on people's land use strategies (Alix-Garcia, Sims et al., 2018; L'Roe et al., 2016), and only very recently has scholars began to consider potential implications for rural livelihoods (Jung et al., 2017; Rasmussen et al., 2017).

Given the limitations found of existing evaluations of Zero Hunger and CAR, these are insufficient as the basis for a full evaluation and holistic exploration of effects and trade-offs that may occur across multiple outcomes across Brazil. Instead, this thesis relies on own analyses based on secondary publically available data and primary data collected in Brazil in 2016 and beginning of 2017. These analyses set out to quantify the (causal) effects, and trade-offs of the Zero Hunger and CAR programmes. Studies have emerged which tries to quantify the trade-offs between multiple sustainability outcomes and the SDGs (Mainali et al., 2018; Spaiser et al., 2017). However, quantifying multiple (casual) social and environmental effects and trade-offs of interventions using large-N data remains scarce. This has resulted in a lack of a proper understanding and accounting of trade-offs across different sustainability outcomes, which further has resulted in incoherent policies and adverse impacts of policies across sectors, and ultimately delayed outcomes leading to sustainable development (Blanc, 2015).

Testing for causal effects of a programme is inherently difficult. A fundamental problem with causal inference based on programmes implemented in the real world is that we can only observe one scenario at a time, i.e. the observation under examination has either participated or not participated in the programme in question, but never both (Imbens & Wooldridge, 2009). The question then becomes how can we, despite this, know the true effect of participation? The randomization criteria in randomized controlled experiments ensures that treated and control groups (i.e. participants and non-participants) are only randomly different from one another on both observed and unobserved background covariates. If this assumption is met, the difference in outcome between treated and control groups can be said to be the causal effect (Ibid.). However, randomized assignment of a policy or programme can be costly and in many cases also unethical (Athey & Imbens, 2017), e.g. preventing a poor family from participating in a social protection programme so it can serve as a control unit. Instead interventions are more often targeted at a particular target population, and they may inhabit certain characteristics which interacts with the outcome in a certain way. This is commonly knows as *selection bias* (Guo & Fraser, 2015).

As a more viable alternative, numerous statistical econometric tools have emerged that aim to correct for underlying covariate differences and biases, caused by confounding variables so that causal effects can be inferred. Popular econometric methods are instrumental variable approach, difference-in-differences, and propensity score matching or weighting. Their individual applicability is mainly driven by the nature of the data with which the method will be used.

The instrumental variable approach has been a widely practiced method in economic research (Guo & Fraser, 2015). It solves the problem of selection bias through a two-stage least squares estimator which estimates the regression coefficients and treatment effects based on an observed (instrumental) variable, which is not correlated with the residual term but is highly correlated with the independent variable (i.e. treatment variable). Finding such instrumental variables in practice is, however, challenging (Guo & Fraser, 2015). The use of instruments is further complicated when there is heterogeneity in the effect of the treatment (Imbens & Wooldridge, 2009). Difference-in-differences methods (DID) have also become a widespread method in policy evaluation (Ibid.). This method requires an outcome to be observed for units in two groups (treated and control) at baseline (before the intervention was launched) and after the intervention is implemented. Basically, the average gain over time in the control group is then subtracted from the gain in the treatment group, and effectively biases caused by both differences between control and treatment groups and biases caused by differences between the two time points are dealt with (Imbens & Wooldridge, 2009). However, if the programme in question is universally implemented in the second time point, DID methods cannot be used.

Matching methods (many of which relies on propensity scores) is another group of increasingly popular econometric methods (Stuart, 2010). These methods aim to solve the selection bias problem by identifying and matching treated and control units, which are similar (or "balanced") with respect to observed covariates. These observed covariates are often expressed through each units' propensity score, defined as the probability of the unit in receiving the treatment given the observed covariates (Stuart, 2010). When participation in the programme can be measured in binary terms (e.g. treated versus non-treated), matching methods are particularly appropriate. Matching methods are not appropriate for multi-level or continuous treatments, because of the difficulty in achieving and assessing the balancing between multiple groups. Because most propensity score matching methods are confined to a binary treatment variable many researchers have ended up dichotomizing a multi-level treatment variable in order to use these methods. At best this can result in the loss of information and potentially important insight, and at worst, result in wrongful conclusions of programme effects (Fong et al., 2017).

Due to the limitations of matching methods to a binary treatment, important recent work has been carried out to develop generalized covariate balancing propensity scores applicable to continuous treatments (Fong et al., 2017; Zhang et al., 2016). In particular the Covariate Balancing Generalized Propensity Score (CBGPS) developed by Fong et al. (2017) deserves a special mention. The CBGPS method deals with selection bias by directly reducing the correlation between treatment level and potentially confounding factors. Basically, it mimics the experimental condition of randomness. Achieving correlation reduction is done by creating inverse generalized propensity score weights, which can subsequently be used in regression methods (Fong et al., 2017). Because it is able to accommodate a continuous treatment variable researchers do not have to loose valuable information as a result of dichotomization. The method also does not require the researcher to select specific methods to achieve the lowest possible correlation (as binary matching methods require) but it calculates the lowest correlation directly. In addition, the CBPGS method has been shown to be both efficient and robust to model misspecification (in either the propensity score or subsequent outcome model) compared to other propensity scores (Fan et al., 2016).

Outside of the econometrics literature, mixed effects models is another popular alternative when attempting to make causal inferences. These models are particularly popular in ecological studies (Harrison et al., 2018). In particular they deal with pseudo-replication (i.e. non-independent observational units) and clustered data by allowing for both fixed and random effects. These models are, however, inherently complex (both to implement and to interpret) and are particularly relevant when the data only represents a small sub-sample of the full study system (Ibid.).

In this thesis, the CBGPS method is used to evaluate multiple effects of both Zero Hunger and CAR. In addition to the benefits of the method described above, the nature of the data meant this was the most appropriate method. For instance, the instrumental variable- and DID methods were inappropriate because of the lack of clear instrumental variables, and because both programmes are universally implemented and subsequently no control units existed. In addition, because the studies carried out in this thesis is based on data for almost the entire study system (e.g. the Zero Hunger study covering 74-97% of all rural municipalities), a mixed effects model was less relevant. Lastly, because continuous information was available for the level of both Zero Hunger and CAR participation, a CBGPS method was more appropriate than alternative matching methods.

2. Thesis overview

The over-arching goal of this research is to explore the effects of current social and environmental protection programmes. In particular it focuses on the possible role of small-scale farmers in simultaneously delivering social and environmental outcomes. The aim is that the knowledge gained in this thesis can help inform future efforts in the struggle to achieve universal sustainable development. In addition to the introductory chapter presented here I present three chapters, written as individual papers intended for publication. I end with a concluding discussion chapter. I also append a published book review since the review directly relates to the topic of the thesis.

Following this introductory chapter, Chapter 2 provides a large-scale analysis of the Zero Hunger programme using publicly available secondary data for all rural municipalities across Brazil. It focuses on the heterogeneous impacts of the Zero Hunger programme overall (defined as the investment in Zero Hungers' four main sub-programmes Bolsa Familia, PRONAF, PAA and PNAE), and the impacts of its two main sub-programmes Bolsa Familia and PRONAF, on food production, multi-dimensional poverty, malnutrition and mortality and natural vegetation loss. Chapter 3 focuses on three municipalities in the state of Minas Gerais, situated in the Mata Atlantica and Cerrado biomes. This case study explores i) if participation in Zero Hunger and its core sub-programmes Bolsa Familia, PRONAF and PAA is influenced by the characteristics of farms and their households, ii) how such participation influences food security (household food insecurity, food access and self-sufficiency) and environmental sustainability (use of agro-chemicals and loss of natural vegetation), and iii) if main farm and household characteristics mediate the impact of participation in Zero Hunger.

Chapter 4 focuses on the CAR programme. Based on secondary data on municipalities within the states of Para and Mato Grosso (situated in the Amazon and Cerrado biomes), it tests whether the programme has affected various land uses which are likely to influence natural vegetation, i.e. change in area under crop and pasture. This chapter also explores the possible mechanisms through which effect has occurred, in particular access to agricultural credit and main commodity markets, and municipal compliance with CAR deforestation criteria, and it distinguishes between effects in municipalities with primarily small-scale and large-scale properties registered under CAR. Finally, Chapter 5 summarises the main findings of this research and comes with a set of recommendations for achieving sustainable development through social protection and environmental programmes which target small-scale farmers.

3. References.

Agência IBASE. (2008). Repercussões do programa Bolsa Família na segurança alimentar e nutricional das Familias beneficiadas. Rio de Janeiro.

Alix-Garcia, J., & Gibbs, H. K. (2017). Forest conservation effects of Brazil's zero deforestation cattle agreements undermined by leakage. *Global Environmental Change*, *47*(August), 201–217. http://doi.org/10.1016/j.gloenvcha.2017.08.009

Alix-Garcia, J. M., Sims, K. R. E., Orozco-olvera, V. H., & Costica, L. E. (2018). Payments for environmental services supported social capital while increasing land management. *Proceedings of the National Academy of Sciences*, 1–6. http://doi.org/10.1073/pnas.1720873115

Altieri, M. a., Funes-Monzote, F. R., & Petersen, P. (2011). Agroecologically efficient agricultural systems for smallholder farmers: contributions to food sovereignty. *Agronomy for Sustainable Development*, *32*(1), 1–13. http://doi.org/10.1007/s13593-011-0065-6

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

Athey, S., & Imbens, G. (2017). The State of Applied Econometrics - Causality and Policy Evaluation. *Journal of Economic Perspectives*, *31*(2), 3–32. http://doi.org/10.1257/jep.31.2.3

Azevedo, A. A., Rajão, R., Costa, M. A., Stabile, M. C. C., Macedo, M. N., dos Reis, T. N. P., … Pacheco, R. (2017). Limits of Brazil's Forest Code as a means to end illegal deforestation. *Proceedings of the National Academy of Sciences*, 201604768. http://doi.org/10.1073/pnas.1604768114

Barbier, E. B., & Burgess, J. C. (2017). The Sustainable Development Goals and the systems approach to sustainability. *Economics*, *11*, 1–22.

Barrientos, A. (2012). Social Transfers and Growth : What Do We Know ? What Do We Need to Find Out ? *World Development*, *40*(1), 11–20. http://doi.org/10.1016/j.worlddev.2011.05.012

Barrientos, A. (2017). Design and rural context in antipoverty transfers: Implications for programme outcomes. *Global Food Security*, *12*(March 2016), 103–108. http://doi.org/10.1016/j.gfs.2016.09.002

Basu, A. K. (2013). Impact of rural employment guarantee schemes on seasonal labor markets : optimum compensation and workers ' welfare. *Journal of Economic Inequality*, *11*, 1–34. http://doi.org/10.1007/s10888-011-9179-y

Beddington, J. R. (2009). *Food, energy, water and the climate: a perfect storm of global events? Conference presentation given to the Sustainable Development UK Annual Conference, QEII Conference Centre, London, 19 March 2009*.

Berdegué, J. a, & Fuentealba, R. (2011). Latin America: The state of smallholders in agriculture. *Paper Presented at the IFAD Conference on New Directions for Smallholder Agriculture, Session 3*, 37. Retrieved from http://193.194.138.127/events/agriculture/doc/papers/berdegue.pdf

Berti, P. R., Krasevec, J., & Fitzgerald, S. (2003). A review of the effectiveness of agriculture interventions in improving nutrition outcomes. *Public Health Nutrition*, *7*(November 2001), 599–609. http://doi.org/10.1079/PHN2003595

Blanc, D. Le. (2015). *Towards Integration at Last? The Sustainable Development Goals as a Network of Targets*. New York, NY, USA.

Bruggeman, D., Meyfroidt, P., & Lambin, E. F. (2015). Land Use Policy Production forests as a conservation tool : Effectiveness of Cameroon ' s land use zoning policy. *Land Use Policy*, *42*, 151–164.

Castaneda, R. (2012). *Zero Hunger: The Brazilian experience*. Rome. Retrieved from http://www.un.org/en/zerohunger/challenge.shtml

Cecchini, S., & Madriaga, A. (2011). *Conditional Cash Transfer Programmes: The recent experience in Latin America and the Carribbean*. Cuadernos de la CEPAL.

CFS. (2012). *Coming to terms with terminology: Food security, nutrition security, food security and nutrition, food and nutrition security*.

Chappell, M. J., & LaValle, L. A. (2011). Food security and biodiversity: Can we have both? An agroecological analysis. *Agriculture and Human Values*, *28*(1), 3–26. http://doi.org/10.1007/s10460-009-9251-4

Chmielewska, D., Souza, D., & Lourete, A. A. (2010). *O programa de aquisição de Alimentos da Agricultura Familiar (PAA) e as práticas dos agricultores participantes orientada ao mercado: Estudo de caso no estado de Sergipe*. Brasilia.

Coates, J. (2013). Build it back better: Deconstructing food security for improved measurement and action. *Global Food Security*, *2*(3), 188–194. http://doi.org/10.1016/j.gfs.2013.05.002

Cunha, W. A. da, Freitas, A. F. de, & Salgado, R. J. dos S. F. (2017). Efeitos dos Programas Governamentais de Aquisição de Alimentos para a Agricultura Familiar em Espera Feliz, MG. *Revista de Economia e Sociologia Rural*, *55*(3), 427–444.

Devereux, S. (2016). Social protection for enhanced food security in sub-Saharan Africa. *Food Policy*, *60*, 52–62. http://doi.org/10.1016/j.foodpol.2015.03.009

Devereux, S., Sabates-Wheeler, R., Guenther, B., Dorward, A., POULTON, C., & Al-Hassan, R. (2008). *Linking Social Protection and Support to Small Farmer Development*. Rome.

Doretto, M., & Michellon, E. (2007). Avaliação dos Impactos Econômicos, Sociais e Culturais do Programa de Aquisição de Alimentos no Paraná, (43), 107–138. Retrieved from http://www.iapar.pr.gov.br/arquivos/File/zip_pdf/aval_impact_econo.pdf

Fan, J., Imai, K., Liu, H., Ning, Y., & Yang, X. (2016). Improving Covariate Balancing Propensity Score : A Doubly Robust and Efficient Approach. *Princeton University*, 1–47.

FAO. (2014). *The state of food insecurity in the world*. Rome. Retrieved from http://www.sidalc.net/cgi-bin/wxis.exe/?IsisScript=LVV.xis&method=post&formato=2&cantidad=1&expresion=mfn=002

054

FAO. (2018). SOFI 2018 - The State of Food Security and Nutrition in the World. Retrieved September 27, 2018, from http://www.fao.org/state-of-food-security-nutrition/en/

Fischer, J., Abson, D. J., Bergsten, A., Collier, N. F., Dorresteijn, I., Hanspach, J., … Senbeta, F. (2017). Reframing the Food – Biodiversity Challenge. *Trends in Ecology & Evolution*, *32*(5), 335–345. http://doi.org/10.1016/j.tree.2017.02.009

Fong, C., Hazlett, C., & Imai, K. (2017). Covariate Balancing Propensity Score for a Continuous Treatment : Application to the Efficacy of Political. *Forthcoming in Annals of Applied Statistics*.

Fraundorfer, M. (2013). Zero hunger for the world: Brazil´s global diffusion of its Zero Hunger strategy. *Austral: Brazilian Journal of Strategy & International Relations*, *2*(4), 91–116.

Gollin, D. (2014). *Smallholder agriculture in Africa: An overview and implications for policy*. London.

Guo, S., & Fraser, M. W. (2015). Counterfactual Framework and Assumptions. In *Propensity Score Analysis: statistical methods and applications* (p. 448). SAGE Publications Ltd.

Harrison, X. A., Donaldson, L., Correa-cano, M. E., Evans, J., Fisher, D. N., Goodwin, C. E. D., … Inger, R. (2018). A brief introduction to mixed effects modelling and multi-model inference in ecology. *PeerJ*, 1–32. http://doi.org/10.7717/peerj.4794

Hazell, P., Poulton, C., Wiggins, S., & Dorward, A. (2007). *The Future of Small Farms for Poverty Reduction and Growth*. Washington, DC.

Imbens, G. W., & Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature*, *47*(1), 5–86. http://doi.org/10.1257/jel.47.1.5

Ingram, J. (2011). A food systems approach to researching food security and its interactions with global environmental change. *Food Security*, *3*(4), 417–431. http://doi.org/10.1007/s12571-011-0149-9

Jayne, T. S., Chamberlin, J., & Muyanga, M. (2014). Emerging Land Issues in African Agriculture : Poverty Reduction Strategies. *Stanford University's Global Food Policy and Food Security Symposium Series*.

Jung, S., Rasmussen, L. V., Watkins, C., Newton, P., & Agrawal, A. (2017). Brazil's National Environmental Registry of Rural Properties: Implications for Livelihoods. *Ecological Economics*, *136*, 53–61. http://doi.org/10.1016/j.ecolecon.2017.02.004

L'Roe, J., Rausch, L., Munger, J., & Gibbs, H. K. (2016). Mapping properties to monitor forests: Landholder response to a large environmental registration program in the Brazilian Amazon. *Land Use Policy*, *57*, 193–203. http://doi.org/10.1016/j.landusepol.2016.05.029

Leite, I. C., Suyama, B., & Pomeroy, M. (2013). *WIDER Working Paper No . 2013 / 022 Africa-Brazil co-operation in social protection Drivers , lessons and shifts in the engagement of the Brazilian Ministry of Social Development*.

Liao, C., & Brown, D. G. (2018). Assessments of synergistic outcomes from sustainable intensification of agriculture need to include smallholder livelihoods with food production and ecosystem services. *Current Opinion in Environmental Sustainability*, *32*(April), 53–59. http://doi.org/10.1016/j.cosust.2018.04.013

Lowder, S. K., Skoet, J., & Raney, T. (2016). The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide. *World Development*, *87*, 16–29. http://doi.org/10.1016/j.worlddev.2015.10.041

Mainali, B., Luukkanen, J., Silveira, S., & Kaivo-oja, J. (2018). Evaluating Synergies and Trade-Offs among Sustainable Development Goals (SDGs): Explorative Analyses of Development Paths in South Asia and Sub-Saharan Africa. *Sustainability*, *10*(815). http://doi.org/10.3390/su10030815

Mercure, J., Paim, M. A., Bocquillon, P., Lindner, S., Salas, P., Martinelli, P., … Vinuales, J. E. (2019). System complexity and policy integration challenges : The Brazilian Energy- Water-Food Nexus. *Renewable and Sustainable Energy Reviews*, *105*(February), 230–243. http://doi.org/10.1016/j.rser.2019.01.045

Mesquita, P. S., & Bursztyn, M. (2017). Food acquisition programs in the Brazilian semi-arid region: benefits to farmers and impacts of climate change. *Food Security*, *9*(5), 1041–1051. http://doi.org/10.1007/s12571-017-0711-1

Meyfroidt, P. (2018). Trade-offs between environment and livelihoods: Bridging the global land use and food security discussions. *Global Food Security*, *16*, 9–16. http://doi.org/10.1016/j.gfs.2017.08.001

Milhorance, C., Sabourin, E. P., & Bursztyn, M. (2015). International Conference of Public Policy Potential and Limits to Diffusing Brazil ' s Zero Hunger Strategy in Sub - Saharan Africa : The Case of Mozambique, (July).

Nazareno, A. G., & Laurance, W. F. (2015). Brazils drought: Beware deforestation. *Science*, (July).

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., … Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, *520*(7545), 45–50. http://doi.org/10.1038/nature14324

Oldekop, J. a., Chappell, M. J., Peixoto, F. E. B., Paglia, A. P., do Prado Rodrigues, M. S., & Evans, K. L. (2015). Linking Brazil's food security policies to agricultural change. *Food Security*. http://doi.org/10.1007/s12571-015-0475-4

Oldekop, J. A., Sims, K. R. E., Karna, B. K., Whittingham, M. J., & Agrawal, A. (2019). Reductions in deforestation and poverty from decentralized forest management in Nepal. *Nature Sustainability*, *2*, 421–428.

Paes-Sousa, R., Santos, L. M. P., & Miazaki, É. S. (2011). Effects of a conditional cash transfer programme on child nutrition in Brazil. *Bulletin of the World Health Organization*, *89*(7), 496–503. http://doi.org/10.2471/BLT.10.084202

Perfecto, I. Vandermeer, J. and Wright, A. (2009). *Nature's matrix: Linking agriculture, conservation* *and food sovereignty*. London: Earthscan. Retrieved from http://climateandcapitalism.com/2012/10/17/natures-matrix/

Perfecto, I., & Vandermeer, J. (2010). The agroecological matrix as alternative to the land-sparing/agriculture intensification model. *Proceedings of the National Academy of Sciences*, *107*(13), 5786–5791. http://doi.org/10.1073/pnas.0905455107

Piperata, B. A., McSweeney, K., & Murrieta, R. S. (2016). Conditional Cash Transfers, Food Security, and Health: Biocultural Insights for Poverty-Alleviation Policy from the Brazilian Amazon. *Current Anthropology*, *57*(6), 806–826. http://doi.org/10.1086/688912

Poulton, P. H. C., Wiggins, S., & Dorward, A. (2010). The Future of Small Farms : Trajectories and Policy Priorities. *World Development*, *38*(10), 1349–1361. http://doi.org/10.1016/j.worlddev.2009.06.012

Rasella, D., Aquino, R., Santos, C. a T., Paes-Sousa, R., & Barreto, M. L. (2013). Effect of a conditional cash transfer programme on childhood mortality: a nationwide analysis of Brazilian municipalities. *Lancet*, *382*(9886), 57–64. http://doi.org/10.1016/S0140-6736(13)60715-1

Rasmussen, L. V., Jung, S., Brites, A. D., Watkins, C., & Agrawal, A. (2017). Understanding smallholders' intended deforestation behavior in the Brazilian Cerrado following environmental registry. *Environmental Research Letters*, *12*(9). http://doi.org/10.1088/1748-9326/aa7ee5

Rodrigues, A. S. L., Ewers, R. M., Parry, L., Jr, C. S., Balmford, A., Rodrigues, A. S. L., … Balmford, A. (2009). Boom-and-Bust Development Patterns across the Amazon Deforestation Frontier. *Science*, *324*(5933), 1435–1437.

Samberg, L. H., Gerber, J. S., Ramankutty, N., Herrero, M., & West, P. C. (2016). Subnational distribution of average farm size and smallholder contributions to global food production. *Environmental Research Letters*, *11*(12), 1–11. http://doi.org/10.1088/1748-9326/11/12/124010

Sayer, J., Sunderland, T., Ghazoul, J., Pfund, J.-L., Sheil, D., Meijaard, E., … Buck, L. E. (2013). Ten principles for a landscape approach to reconciling agriculture, conservation, and other competing land uses. *Proceedings of the National Academy of Sciences*, *110*(21), 8349–8356. http://doi.org/10.1073/pnas.1210595110

Silva, J. G. da, Grossi, M. E. Del, & França, C. G. de. (2011). *The Fome Zero (Zero Hunger) Program: The brazilian experience*. (J. G. da Silva, M. E. Del Grossi, & C. G. de França, Eds.). Brasilia.

Soares, F. V., Ribas, R. P., & Osorio, R. G. (2010). Evaluating the Impact of Brazil's Bolsa Familia: Cash transfer programs in comparative perspective, *45*(2), 173–190.

Spaiser, V., Ranganathan, S., Swain, R. B., & David, J. T. (2017). The sustainable development oxymoron : quantifying and modelling the incompatibility of sustainable development goals. *International Journal of Sustainable Development & World Ecology*, *24*(6), 457–470. http://doi.org/10.1080/13504509.2016.1235624

Stuart, E. a. (2010). Matching Methods for Causal Inference: A Review and a Look Forward, *25*(1), 1–21. http://doi.org/10.1214/09-STS313

Thorkildsen, K. (2014). Social-Ecological Changes in a Quilombola Community in the Atlantic Forest of Southeastern Brazil. *Human Ecology*. http://doi.org/10.1007/s10745-014-9691-3

Tscharntke, T., Clough, Y., Wanger, T. C., Jackson, L., Motzke, I., Perfecto, I., … Whitbread, A. (2012). Global food security, biodiversity conservation and the future of agricultural intensification. *Biological Conservation*, *151*(1), 53–59. http://doi.org/10.1016/j.biocon.2012.01.068

Tubiello, F. N., Salvatore, M., Ferrara, A. F., House, J., Federici, S., Rossi, S., … Smith, P. (2015). The Contribution of Agriculture, Forestry and other Land Use activities to Global Warming, 1990-2012. *Global Change Biology*, *21*(7), 2655–2660. http://doi.org/10.1111/gcb.12865

UNCTAD. (2015). Commodities and Development Report 2015: Smallholder Farmers and Sustainable Commodity Development. *United Nations Conference on Trade and Development*, 1–20. http://doi.org/UNCTAD/SUC/2014/5

Webb, P., & Kennedy, E. (2014). Impacts of agriculture on nutrition : Nature of the evidence and research gaps. *Food and Nutrition Bulletin*, *35*(1), 126–132. http://doi.org/10.1177/156482651403500113

Winters, P., & Davis, B. (2009). Designing a programme to support smallholder agriculture in Mexico: Lessons from PROCAMPO and Oportunidades. *Development Policy Review*, *27*(5), 617–642. http://doi.org/10.1111/j.1467-7679.2009.00462.x

Wittman, H., & Blesh, J. (2017). Food Sovereignty and Fome Zero: Connecting Public Food Procurement Programmes to Sustainable Rural Development in Brazil. *Journal of Agrarian Change*, *17*(1), 81–105. http://doi.org/10.1111/joac.12131

Zhang, Z., Zhou, J., Cao, W., & Zhang, J. (2016). Causal inference with a quantitative exposure. *Statistical Methods in Medical Research*, *25*(1), 315–335. http://doi.org/10.1177/0962280212452333

Chapter 2

Assessing multi-dimensional sustainability: lessons from Brazil's Zero Hunger social protection programmes

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Abstract

Examining linkages between multiple sustainable development outcomes is key for understanding transitions to sustainability. Yet rigorous evidence using large-N data on multiple social and environmental outcomes of sustainable development policies remains scarce. We conduct a comprehensive, national-level analysis of Brazil's flagship social protection programme, Zero Hunger, which aims to improve food security and alleviate poverty. Using data from over 3,800 rural municipalities and quasi-experimental causal inference techniques, to control for non-random treatment allocation, we assess relationships between Zero Hunger investment and three sets of outcomes that relate to divergent but inter-linked sustainable development goals (SDGs): 'no poverty' (SDG 1), 'zero hunger' (SDG 2) and 'health and well-being' (SDG 3). We also check for potential perverse outcomes that may arise if programmes promote agricultural expansion that increases clearance of natural vegetation - which would adversely impact 'climate action' (SDG 13) and 'life on land' (SDG 15). We find that despite increasing daily per capita protein and kilocalorie availability, overall investment in Zero Hunger did not alleviate child malnutrition or infant mortality and had smaller impacts on multi-dimensional poverty. Impacts of investment on the loss of natural vegetation varied across biomes, with higher investment increasing cover in some biomes but increasing losses elsewhere, especially the Pampa but the Cerrado and Amazon are also vulnerable. Effects varied substantially across programme components: the conditional cash-advance Bolsa Familia tended to be associated with non-beneficial impacts, while the agricultural-supportive PRONAF was associated with increased food production, poverty alleviation and changes in natural vegetation. Our results inform development of policies to meet multiple SDGs by highlighting successful elements of Brazil's Zero Hunger programme, variable outcomes across divergent food security dimensions, and linkages and trade-offs between divergent sustainable development goals, including environmental protection.

1. Introduction

Sustainability requires balancing human development with environmental integrity (Loos et al., 2014). It is an elusive societal goal requiring transitions across multiple dimensions - including food security, poverty alleviation, health and environmental protection. These major global challenges interact and at times trade-off with each other (Meyfroidt, 2018), and are reflected in national development plans and international sustainability agendas, including the Sustainable Development Goals (SDGs).

Food insecurity (reflected in SDG 2) remains an intractable global problem (FAO et al., 2017). Addressing it is complicated by the need to meet multiple food system components 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 (CFS, 2012). Food security is thus directly linked to both poverty alleviation (SDG 1), and health and well-being (SDG 3) (Benton, 2016). Yet, agricultural production and expansion are also key drivers of natural vegetation and biodiversity loss (SDG 15), and greenhouse gas emissions (SDG 13) (Newbold et al., 2015; Tubiello et al., 2015). These environmental changes can, in turn, negatively feedback to affect agricultural production (Mercure et al., 2019; Nazareno & Laurance, 2015).

Systems-based approaches to meeting global challenges aim to understand, account for, and measure such interdependencies, synergies and trade-offs (Ingram, 2011; Liao & Brown, 2018). While these linkages are a key focus of scholarly work and policy discussions around the globe, efforts to quantify synergies and trade-offs across multiple dimensions of sustainability remain rare (Loos et al., 2014; Meyfroidt, 2018).

Here, we assess how Brazil's flagship social protection programme, Zero Hunger, has affected food production, poverty, malnutrition and mortality, and changes in natural vegetation cover. National development strategies frequently focus on social protection programmes to support livelihoods, alleviate income or food poverty, and manage vulnerability to shocks (Devereux, 2016). Understanding how these programs affect multiple aspects of sustainability is critical, yet they are often designed (and evaluated) as single instruments with specific aims and target populations (e.g., the effect of unconditional cash transfers on household poverty, or the effect of input subsidies on food production (Devereux, 2016)). Evaluations rarely asses outcomes not explicitly stated as programme objectives (Barrientos, 2012; Sayer et al., 2013). This narrow focus increases the potential for trade-offs and perverse outcomes to remain undetected, potentially generating incomplete and misleading conclusions on programme and policy effectiveness (Coates, 2013; Liao & Brown, 2018).

In our assessment of Zero Hunger, we combine a suite of high-resolution datasets and use quasi-experimental causal inference techniques to control for non-random treatment allocation. Our analysis provides 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 many programmes are partly based on Zero Hunger (Fraundorfer, 2013).

Brazil's Zero Hunger Programme

Zero Hunger has been Brazil's flagship social protection programme aiming to tackle food security, poverty and inequality. It is considered a key mechanism through which Brazil met the Millennium Development Goal of halving extreme poverty and hunger by 2015 (Castaneda, 2012). The programme launched in 2003 with the aim of lifting 44 million poor Brazilians out of poverty and food insecurity (Silva et al., 2011). It is is embedded within a larger national food and nutrition security policy and is funded via the national government who allocate money to state or municipal governments, and in some instances directly to programme beneficiaries (e.g. Bolsa Familia transfers). In Brazils' decentralized government system much of the oversight, training of staff and funding decisions are made at the state level, whereas implementation falls primarily at the municipal level – the smallest administrative unit in Brazil (Silva et al., 2011).

Zero Hunger is an umbrella programme that includes four primary sub-programmes, which at the time of Zero Hunger's inception received approximately 90% of the programmes' total budget (Silva et al., 2011). Small family run farms are the primary programme targets, due to their key role in rural development and national food security (Kepple et al., 2014; Samberg et al., 2016). 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 Programme* (PAA). Zero Hunger defines family farms as those that use family labour and are less than four fiscal modules in size (one fiscal module represents the area required to ensure economic viability of a rural establishment - this metric varies in size across Brazil to account for different land quality (Assunção et al., 2013)). The markets created through PAA are operated by state-linked institutions that buy produce directly from local farmers to supply social assistance programmes, government funded schools and local markets (Rocha, Burlandy, & Maluf, 2012). A dominant social assistance programme is iii) *The National School Feeding Programme* (PNAE) which provides free school meals to all children (Sidaner et al., 2013). Finally, families in poverty, many of which operate small family run farms, qualify for monthly cash transfers through iv) *The Bolsa Familia* sub-programme, conditional on child school attendance and participation in family health check-ups and vaccination programmes (Leão & Maluf, 2013).

The Zero Hunger programme thus provides an integrated system-based policy initiative with the potential to influence rural livelihoods and food security, health outcomes, agricultural production, and land-use change. Zero Hunger has been associated with increased farm incomes (Doretto & Michellon, 2007), increased food purchases in food insecure households (Agência IBASE, 2008), reduced child malnutrition (Paes-Sousa et al., 2011), and lower infant mortality (Rasella et. al, 2013). Yet some evidence also suggests that Zero Hunger has had negligible effects on agricultural production, farmer livelihoods, child malnutrition and long-term food security (Oldekop et al., 2015; Piperata et al., 2016; Thorkildsen, 2014). All these evaluations are limited, however, by a failure to consider spatial heterogeneities and key confounding factors. Each of these studies also focuses on a narrow range of outcomes preventing full evaluation and exploration of the synergies and trade-offs that may occur across multiple sustainable development objectives. Crucially, there has been negligible assessment of Zero Hunger's impact on natural vegetation cover (Thorkildsen, 2014).

Analytical approach

We use a quasi-experimental approach to assess Zero Hungers' effect on food production, poverty, malnutrition, health and changes in natural vegetation cover. We combine publicly available data from national and global sources (see Materials and Methods and SI Appendix for specific sources) to create a high-spatial resolution longitudinal dataset for over 3,800 rural municipalities (covering 74-97% of all rural municipalities). These areas are where small family run farms (Zero Hunger's primary beneficiaries) are concentrated and in which almost all natural vegetation loss has occurred.

We first analyse the impact of total financial investment cumulated across Zero Hunger's four main sub-programmes: PRONAF, PAA, PNAE and Bolsa Familia, and then separately assess the impacts of the two largest sub-programmes, Bolsa Familia (capturing 46% of our total Zero Hunger investment value) and PRONAF (capturing 42% of our total Zero Hunger investment value). These two sub-programmes provide examples of two frequently adopted and complementary approaches to social protection programmes: cash transfer to protect minimum subsistence (Bolsa Familia) and credit provision to support household investment and livelihood diversification (PRONAF) (Devereux, 2016). Total financial investment is expressed as investment per capita, based on the total municipal population. We assess impact on changes in multi-dimensional poverty (relating to SDG 1), food production (SDG 2) expressed as daily kilocalorie and protein production per capita, child malnutrition (the proportion of children underweight (SDG 1 and 3)), infant mortality (SDG 3) and area (km^2) under natural vegetation cover (SDGs 13 & 15).

We measure change from 2004 (the first complete year of the Zero Hunger programme) to 2013 (the most recent year with information across all predictor variables at the time of analysis), and for poverty and infant mortality additionally from 2000 to 2010. We use two separate datasets for poverty and infant mortality that represent the i) entire municipal population through the national demographic census (2000 – 2010), and ii) a poorer and more deprived sub-sample of the population using data from the national primary information system (SIAB; 2004-2013; Rasella et al., 2010).

To assess the link between investment and changes in outcomes, we use the covariate balancing generalized propensity score (CBGPS) method. This method reduces potential bias caused by non-random treatment allocation by reducing the correlation between treatment and potential confounding factors (Fong et al. 2017) (see Materials and Methods and SI Appendix for more details). We model outcomes in the final year of the evaluation period as a function of total per capita investment in Zero Hunger (R$). We account for inflation (IGP-DI index, base year 2013) and control for key confounding predictor variables (capturing 14 biophysical and socio-economic factors and baseline conditions; see Materials and Methods and SI Appendix for more information).

Our statistical models include quadratic terms to account for potential non-linear effects (small cash transfers can potentially have large effects on poor households - Barrientos, 2012), as well as interaction effects between investment, and state or biome to account for potential regional variations in programme implementation (state interaction effects) (Silva et al., 2011) and environmental differences (biome interaction effects; (MMA, 2007)). See Table S1 for a complete list of all model parameters. We also use our regression models to predict and visualize change in our outcome variables resulting from different investment scenarios (negligible investment, actual investment and spatially uniform investment – see Materials and Methods) and non-linear effects. We also conduct several robustness checks that assess if our inferences still apply when excluding lower quality data and to ensure that they are not unduly influenced by endogeneity and spatial autocorrelation (Materials and Methods and SI Appendix).

2. Results

We find considerable heterogeneity in the impact of Zero Hunger investment. This variation arises for three primary reasons. First, impacts vary across our outcome variables with evidence for positive, negligible and negative impacts depending on the outcome variable. Second, within a single outcome variable investment impacts vary depending on if investment is delivered via cash transfer programmes (Bolsa Familia) or agricultural credit (PRONAF). Finally, within a single outcome variable and investment mechanism there is considerable spatial variation in the magnitude and even direction of impact (Fig. 1). This is partly simply a consequence of spatial variation in the magnitude of investment (Fig. S2), but when modelling impacts with a spatially uniform per capita level of investment, marked spatial variation in outcome often remains (Fig. S1).

Food production

Actual investment in Zero Hunger increased daily per capita protein production across Brazil (Table 1), but kilocalorie production only increased in five of Brazil's 26 states (Fig. 1). We find substantial spatial variation driven by differing levels of investment as well as trade-offs between kilocalorie and protein production associated with, in particular, BF investment.

Investment in PRONAF was associated with increased per capita protein and kilocalorie production across most of Brazil. Increases in both outcomes are most marked in the south of the country. Yet, these increases appear to be mostly driven by higher investment levels in this region (Fig. S2). When modelling spatial variation of impacts with a spatially uniform level of investment (Fig. S1) the effectiveness of PRONAF on per capita protein and kilocalorie production in the north-east (a region characterized by difficult climatic and socio-economic conditions and low productivity of family farms

(Guanziroli et al., 2012; Sietz et al., 2006)) is almost equal to that found in the south (a region where family farms have traditionally had more access to credit and technical assistance (Helfand et al., 2015), and generally productivity levels are high (Guanziroli et al., 2012)). While family farmers in the south have traditionally participated more actively in larger national and international markets such as soybean, rice and beef (Oliveira et al., 2017), family farmers in the north-east contribute greatly to local and national production of staple foods such as rice, maize and cassava (Guanziroli et al., 2012). Thus, diverting some PRONAF funds from the south to the north-east could potentially be particularly cost-effective and beneficial for food security, especially considering that the farmers in the north-east produce primarily for local and national food markets.

Bolsa Familia had a larger effect than PRONAF on per capita protein production – with actual levels of Bolsa Familia investment increasing production by on average 125% (SE = 5.1) across municipalities compared to PRONAF's average increase of 37% (SE = 0.81). This difference was driven by particularly large PRONAF impacts in some states (e.g. Alagoas). Notably, BF investment appears to be more effective in the north and north-east (Fig. 1). Considering that these two regions had low levels of daily per capita protein production at baseline (Fig. 1) and historically suffer from high food insecurity (Kepple et al., 2014), Bolsa Familia appears particularly well targeted here. The increases in income provided by Bolsa Familia (representing ~46% of household income for extremely poor agricultural households - Osorio et al., 2011) have likely enabled rural households to invest parts of the transfer in agriculture. Cash-transfer programmes in Mexico have been found to have similar effects (Todd et al., 2010).

Despite positive effects of Bolsa Familia on protein production, we find that it is associated with a reduction in kilocalorie production, especially in north-eastern and south-eastern regions (Fig 1). These spatial patterns persist when we model these impacts with a spatially uniform level of investment (Fig. S2). Maize, rice and cassava are main contributors to per capita kilocalorie production in regions where Bolsa Familia is associated with reduced per capita kilocalorie production, with our production data indicating that productions of these crops in these regions has declined by 30-40%, whilst milk and livestock production have increased respectively by 25% and 8%. BF may thus be encouraging small-scale farmers to reduce production of traditional staple crops rich in carbohydrate (and thus calories), such as cassava, and shift to livestock. Some farmers may also scale back production and use cash transfers to purchase food, as reported in localised studies (Thorkildsen, 2014), which could reduce resilience to food price shocks.

Table 1. Impacts of per capita Zero Hunger, Bolsa Familia and PRONAF investment on food production, poverty, health and malnutrition, and natural vegetation cover

	Zero Hunger				Bolsa Familia				PRONAF			
Outcome	Coef±S.E.	P	Int.	R^2	Coef±S.E.	P	Int.	R^2	Coef±S.E.	P	Int.	R^2
Kcalories^{pc}	-0.01±0.02	0.48	S	0.94	-0.05±0.02	0.02	S	0.93	0.04±0.01	0.002	S	0.94
Protein^{pc}	0.06±0.02	0.001	S	0.96	0.08±0.02	<0.0001	S	0.95	0.04±0.01	<0.001	S	0.96
Poverty^{Census}	-0.006±0.006	0.38	S	0.76	0.03±0.01	0.01	S	0.76	-0.02±0.004	<0.0001	S	0.77
Poverty^{Census} (quadratic)	-0.007±0.002	0.001										
Poverty^{SIAB}	0.01±0.01	0.6		0.61	0.06±0.02	<0.001		0.62	0.001±0.01	0.88	S	0.61
Child Malnutrition^{SIAB}	0.12±0.04	0.002			0.31±0.14	0.03	S		-0.05±0.03	0.10		
Infant Mortality^{Census}	0.01±0.23	0.97		0.14	0.01±0.27	0.97		0.25	-0.01±0.23	0.96		0.14
Infant Mortality^{SIAB}	0.005±0.05	0.93			0.14±0.05	0.01		n.a.	-0.04±0.06	0.50		
Natural Veg.^{km2}	-0.01±0.003	<0.0001	B	0.99	-0.01±0.002	0.002		0.99	-0.01±0.003	0.003	B	0.99
Natural Veg.^{km2} (quadratic)	-0.004±0.001	<0.001							-0.003±0.001	0.001		

Outcomes refer to daily per capita (pc) kilocalorie and protein production, 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 and in the poorer sectors (Census and SIAB), and area of natural vegetation. Model coefficients are reported ± one standard error. S and B respectively indicate models that include significant interactions between investment in overall Zero Hunger or its sub-programmes and state or biome (natural vegetation models). 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, 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} using 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.

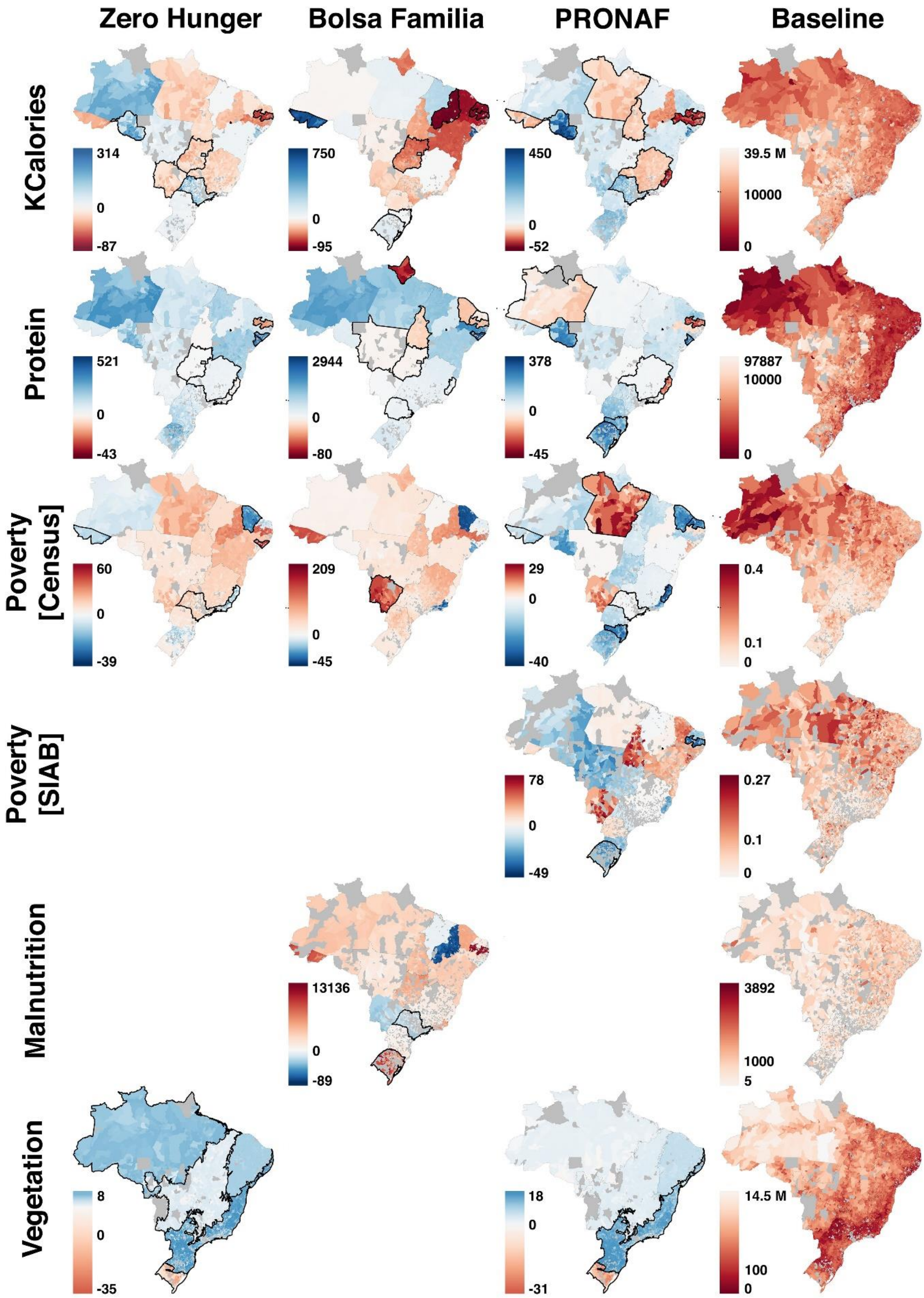


Fig. 1. Relative impact of Zero Hunger, Bolsa Familia and PRONAF investment (column 1-3) on daily per capita kilocalorie production, daily per capita protein production, poverty in the entire population (Census), poverty in the poorer sectors of society (SIAB), child malnutrition in the poorer sectors 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 (1^{st} percentile value) programme investment level and actual total programme investment level. Column 4 shows values of the outcome at baseline (i.e. year 2000 for 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 (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 in rows 1-3 blue indicating beneficial and red non-beneficial impacts. In maps of baseline values (column 4) deeper red indicates municipalities with a worse starting condition, such as high 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

Poverty

We use two measures of poverty - one using SIAB data that focuses on the poorest sub-sample of the population and one based on the national census. We find no association between Zero Hunger investment and poverty in the poorest population, but investment in Bolsa Familia is associated with an increase in poverty in this vulnerable population (Table 1). Investment in PRONAF did not generally influence poverty in the poorest population sub-sample but appeared to reduce this poverty metric in two states (Fig. 1) – but these effects were not detectable when restricting the analysis to the highest quality data (Table S3).

We, do however, find a non-linear association between Zero Hunger investment and our census poverty measure (Table 1). Given actual municipal per capita investment levels (range R$ 145 – 29,132) our models predict an overall 8% (SE = 0.19) increase in general poverty. However, four states across Brazil have experienced a significant reduction (Fig. 1) and with a spatially uniform investment level above R$ 1,752 (the median per capita investment level) overall poverty increases taper off. For estimates based on the quality restricted dataset and under a uniform investment level equivalent to the 95th percentile investment level poverty alleviation is achieved for Brazil overall (Fig. S3). Again, effects found for Zero Hunger overall could be driven by effects from the Bolsa Familia and PRONAF sub-programmes.

Investment in BF was associated with a 24% (SE = 0.45) increase in our census poverty measure (compared to a negligible investment scenario; Table 1). Four states, located in the north-east and south-east, show non-significant trends for BF-linked average reductions in our census poverty measure (Fig. 1). Three of these states (Ceara, Sergipe and Rio Grande do Norte) are found in the poorer north-east, suggesting that in selected areas BF might have driven poverty reductions. We find similar overall adverse impacts with Bolsa Familia investment on our census poverty measure when restricting data to the highest quality dataset (Table S3), however, here a non-linear relationship is found which suggests that although increased BF drives an overall increase in poverty, at lower investment levels BF investment is actually associated with slight poverty alleviation (Fig. S4). In fact, the spatial variation in effect reveals that again north-eastern (and northern) states might have experienced poverty reduction as a result of Bolsa Familia investment, even at higher investment levels, though again there is higher uncertainty around these estimates given that these state effects are not significantly different to the overall effect.

Previous work on BF has shown that it is insufficient to lift households out of poverty. For this to happen households required additional access to cash benefits (e.g. pensions), or labour markets (Osorio et al., 2011). Other research has found that the conditional aspects of BF, particularly those aimed at improving health and nutrition, have failed to deliver their intended aims - primarily due to supply side constraints (Soares et al., 2010) and a lack of monitoring capacity (Araújo et al., 2018). The north-east of Brazil was a key exception to this monitoring challenge (Araújo et al., 2018), which is where we find potential poverty alleviation effects driven by Bolsa Familia.

In contrast to BF, we find that increased PRONAF investment was, on average, associated with reductions in our census poverty measure (Table 1). There is marked spatial variation, with a few states exhibiting increased poverty in association with increased PRONAF investment, and notably selected states in the north, north-east and southern regions exhibited the most marked reductions in census poverty (Fig. 1). The magnitude of effects remain similar under a uniform (median) investment scenario (Fig. S1).

The link between PRONAF and labour markets might help explain the observed PRONAF-driven reductions in our census poverty measure. PRONAF funds must be invested in agricultural production. The scheme thus has the potential to increase both production and associated labour markets. This relationship is also emphasized by Helfand et al. (2015) who highlights the importance of off-farm income for poverty alleviation for farmers. They also suggest that off-farm employment tends to be accessed by more capable (and competitive) farmers (Helfand et al.., 2015), which might explain why we find negligible PRONAF effects on poverty in the poorest sub-sample.

Malnutrition and Mortality

We find no effect of Zero Hunger, or its two main sub-programmes, on our census-derived measure of infant mortality. However, we do find BF-linked increases in infant mortality amongst the poorest sectors (Table 1; Table S3). Similarly, our measure of child malnutrition in the poorest sectors of society increased with investments in Zero Hunger and Bolsa Familia (Table 1). However, these adverse effects were not present when applying data quality controls (Table S3). These patterns thus suggest that investment in Zero Hunger is not improving childhood health. The adverse impacts of BF on per capita food production and poverty (see above) occur alongside and may contribute to its apparent adverse impacts on infant mortality in the poorest sectors of society that are more likely to be vulnerable to reduced food production and increased poverty. Our results build on earlier work conducted at more local scales which suggest that Bolsa Familia has been struggling to deliver on its intended health and nutrition aims (Piperata et al., 2016; Soares et al., 2010), perhaps due to leading to poorer household shifting production away from traditional staple crops (often vital in times of need) and increasing reliance on purchased foods (Piperata et al., 2016; Thorkildsen, 2014).

Natural vegetation cover

Zero Hunger and PRONAF have non-linear impacts on natural vegetation cover, with significant variation across biomes in the nature of these relationships (Table 1). Our models predict that actual levels of investment resulted in increased natural vegetation cover across all biomes except the Pampa. Gains in natural vegetation cover will involve secondary vegetation growth, but the conservation value of such vegetation is increasingly recognised (Barlow et al., 2007; Edwards et al., 2017). Notably, however, due to non-linearities, with Zero Hunger investment levels above the median level (R$ 2,750 per capita) natural vegetation cover gains start tapering off, and at even higher investment levels (e.g. the 95th percentile investment level corresponding to per capita R$ 12,121) in municipalities within the Cerrado biome investment could lead to reduced natural vegetation cover (quantified as average 43 km^2 loss per municipality, equivalent to a 3% reduction in cover compared to a negligible investment scenario; Fig. S5). Likewise, due to non-linearities, a 95th percentile PRONAF investment level (corresponding to per capita R$ 11,316) could lead to at best hardly any further gains in natural vegetation cover in municipalities within the Cerrado and Amazon biomes (based on model restricting data to the highest quality datasets) (Fig. S6). At worst it could lead to reduced vegetation cover (quantified as average 194 km^2 and 3 km^2 loss in cover, equivalent to a 3% and 0.3% reduction in cover compared to a negligible investment scenario), though we note these biome effects are not significantly different to the overall Brazilian effect. Interestingly, PRONAF investments at the 25th, 50th, and 95th percentile levels are all associated with increasing gains in natural vegetation cover (Fig. S6).

Investment in Bolsa Familia appears to drive natural vegetation loss in a linear manner across all biomes (Table 1). When restricting analyses to those municipalities with the highest quality data the effect of investment is reduced but it remains very close to the threshold of statistical significance (Table S3). Our analyses focus on total change rather than fine scale spatial dynamics of loss and gain but clearly indicate that social protection programmes can have divergent and biome specific impacts on natural vegetation in regions that are of major importance for conservation both nationally (as climate regulators and providers of vital ecosystem services that support food production and human wellbeing (Joly et al., 2014; Nazareno & Laurance, 2015) and globally (as global biodiversity hotspots (Myers et al., 2000).

For instance, while our results suggest the southern Pampa biome (a biome characterized by natural grasslands (Overbeck et al., 2007)) has been particularly negatively affected by Zero Hunger (and the PRONAF sub-programme), the neighbouring Atlantic Forest biome (a biome characterized by archipelagos of small tropical forest fragments (Joly et al., 2014)) appear to be particularly positively affected. Both biomes have a long history of disturbance due to agricultural activities. The Pampa has historically suffered from extensive and unsustainable cattle production, leading to heavily degraded natural grasslands, desertification and due to reduced economic return the emergence of other agricultural activities such as soy production (Overbeck et al., 2007). Large tracts of the Atlantic Forest vegetation have been lost to sugar-cane, coffee, cocoa, and in more recent times, cattle ranching (Joly et al., 2014). It is thus interesting that while our results suggest both biomes have experienced increases in food production as a result of Zero Hunger (and PRONAF) investment, it is only in the Pampa biome that this increase appears to have negatively affected natural vegetation cover. It is possible that while investment in the Atlantic Forest has promoted agricultural intensification sparing agricultural land and enabling vegetation regrowth in abandoned and/or more marginal lands, investments in the Pampa has promoted expansion of agriculture and thus promoted loss of natural vegetation. Barretto et al. (2013) found that agricultural intensification particularly in the Atlantic Forest prior to 2006 had indeed resulted in farmland stability or contraction (allowing for re-growth of natural vegetation), and this trend might have continued after 2006, though this study also reported a similar pattern for the south of Brazil (Pampa) (Barretto et al., 2013).

Whether investment promotes intensification or expansion could differ depending on which product it targets, e.g. Assunção et al.(2013) found that credit support to livestock activities drove more conversion of natural vegetation than support for crop production. They argued this was because of the relative ease of expansion compared to intensification (which is arguably easier obtainable within crop production) (Assunção et al., 2013). In addition, Meyfroidt highlight how agricultural production linked to global markets with high demand (e.g. meat and soy) are likely to experience land expansion as a result of improvements in production (Meyfroidt, 2018). Though our food production results suggest that PRONAF has driven particularly high increases in protein production in the state of Rio Grande de Sul (which inhabits the Pampa biome) we cannot say (from our data) whether the investment has been targeted at a specific activity.

Alternatively, the contrasting effects of investment in these biomes could be due to different levels of conservation attention as that can deter farmers from converting natural vegetation into farm land. For instance, whereas the Pampa has received little conservation attention (e.g. no protected areas under categories I to IV of the IUCN exist here) (Overbeck et al., 2007), the Atlantic Forest has received a fair amount of attention from academics and governments (Pinto et al., 2014). Although our analyses take protected area into account, due to data limitations they do not explicitly control for additional local conservation activities or biome-specific conservation efforts (such as the *the Atlantic Forest Restoration Pact* (Pinto et al., 2014), and rather these are embedded within the biome control variable. As such the difference in effect of investment might also be caused by differences in local or biome specific control mechanisms, which can deter farmers from removing natural vegetation with the received Zero Hunger investment, however, more research into possible mechanisms would be useful.

3. Discussion

Our systems approach to evaluating Zero Hunger reveal both synergies and trade-offs. We show that increases in food production do not automatically lead to improvements in food security (child malnutrition) (SDG 2), and that achieving poverty alleviation (poverty) (SDG 1) and improvements in health (infant mortality) (SDG 3) are more difficult to obtain, particularly for the poorer sectors of society. In fact, to achieve an overall reduction in poverty across Brazil Zero Hunger investment would have to be higher in many areas. It also shows that social protection programmes that aim to improve food security, even if they do so without specific objectives to influence land use, can have environmental consequences and influence the amount of natural vegetation cover (SDG 15 and SDG 13). Notably the direction of these unintended impacts vary across biomes and by investment level, with potentials for win-win situations and environmental benefits accruing in some regions in which social benefits also arose from investment in Zero Hunger.

Our results reveal contrasting direction of effects from the two main Zero Hunger sub-programmes Bolsa Familia and PRONAF. Though clearly opposite of the aim of the programme, Bolsa Familia appears to drive increases in poverty and bad health, particularly amongst the poorest sectors of society. PRONAF on the other hand is found to drive reduction in general poverty (though not within the poorest sectors). Osorio et al. (2011) found that Bolsa Familia alone could not lift poor households out of poverty between 2004-2009, for that to happen these families needed access to labour markets or transfers (such as pensions). Meyfroidt (2018) also highlight the importance of employment creation and argue that medium-scale farmers (define as farmers generally between 5 and 100 hectares) have a particular important role to play in food security and poverty alleviation in rural areas because they are particularly able to benefit from agricultural support programmes (such as PRONAF) and they effectively can turn that into employment creation for poorer farmers in need of additional income (Meyfroidt, 2018). We find it possible that the ripple effect as described above has driven PRONAF's poverty alleviation effects across the general population, and note that the main recipient farmers of PRONAF were more what Meyfroidt (2018) defined as medium-scale farmers (Eusebio et al., 2016; Vieira, 2015) than those considered as small-scale farmers in a global sense (i.e. below 2 hectares). However, we also note that PRONAF has not been effective at poverty alleviation or health improvements in the poorest sectors of society, possibly because the poorest farmers are unable to access the newly created jobs as suggested by Helfand et al. (Helfand et al., 2015).

Interestingly, our model scenario results where all municipalities receive an equal amount of PRONAF investment revealed that if given the chance also regions which are less developed and traditionally have had lower agricultural efficiency (e.g. North-East) could generate close to as large relative beneficial effects in both food production and general poverty alleviation as the more developed south. Thus, not only could one argue that focusing the majority of support in the south creates a misalignment in terms of reaching areas most in need, but focusing PRONAF in less developed areas does not have to come at the expense of lower programme effects. We also note that in terms of increasing food (protein) production Bolsa Familia appears particularly well targeted in the North-East, as the by far largest relative beneficial effects on per capita protein production has occurred here. Unfortunately these improvements have not been sufficient to translate into clear improvements in poverty and health from Bolsa Familia, though we do note that some states show non-significant poverty reductions in the general population.

A main contributing reason for the unintended non- beneficial effects from Bolsa Familia on poverty and health could be a failure of appropriate implementation of the conditional aspect of the programme. Particularly in rural impoverished areas a basic level of infrastructure is often incomplete or lacking (Barrientos, 2017), and though often outside the remit of social protection programmes themselves, the presence and quality of such infrastructure is vital for the programmes to be effective (Barrientos, 2017). The conditional aspects of Bolsa Familia are child school attendance and child/mother health check-ups. Thus (at minimum) the presence of institutions like schools and health centres are needed for the conditionalities of Bolsa Familia to be most effective. Their positive impacts on health and well-being is also mediated by household conditions such as presence of sanitation and basic services (Grebmer et al., 2012; Smith & Haddad, 2015). The cost of acquiring such services is more than what a poor household can withstand (with or without Bolsa Familia) and rather to gain access they rely on government investments in basic infrastructure. If public investment for a social protection programme comes at the expense of investments into necessary infrastructure, as has been suggested is the case for Bolsa Familia, this can seriously threaten the effectiveness of these programmes (Hall, 2008; Soares et al., 2010).

Functioning institutions to implement and enforce compliance with the conditionalities are also vital for the success of conditional cash-transfers (Barrientos, 2017). With the implementation of Bolsa Familia the demand for, and pressure on, existing health and education services has risen (Araújo et al., 2018), particularly in highly populous areas and/or areas with a large proportion of Bolsa Familia beneficiaries. In such areas the monitoring of conditionalities (health in particular) have been found particularly challenging (Ibid.). Added pressure on existing services caused by conditional cash transfer programmes can also negatively impact the larger community as the capacity to offer quality services under this added pressure might be severely reduced (Schüring, 2010).

These are thus likely contributing factors to why we find non-beneficial effects of Bolsa Familia on poverty and health. As such, even though the interventions themselves have no direct bearing on neither the presence nor quality of these conditions, the successfulness of the intervention ultimately may depend on them. Currently the Zero Hunger programme is being rolled out to other developing countries, many in Sub-Saharan African where public funding may be limited and basic infrastructure and functioning institutions are often lacking (Devereux, 2016; Dorward et al., 2009). This runs the risk of reduced effectiveness. On the other hand, many Sub-Saharan African countries still face chronic hunger and bad health due to low food production (Ingram, 2011). As such, interventions like Bolsa Familia might generate beneficial effects on health there given that the programme has shown able to increase food production particularly in poorer areas.

Our results also show that social protection programmes may have unintended environmental impacts, particularly in the southern Pampa biome. How social protection programmes drive environmental outcomes is much less explored than the opposite, i.e. how land use and environmental programmes can impact livelihoods (Liao & Brown, 2018). This is especially the case for programmes with no obvious direct link to land use, e.g. Bolsa Familia (from which we find a slight negative effect on natural vegetation cover). However, some research have found social cash transfer programmes can influence both agricultural production and land use by changing social relations around farming (Piperata et al., 2016; Thorkildsen, 2014) or by reducing liquidity constraints to farming (Barrientos, 2017; Todd et al., 2010), and even resulted in deforestation (Alix-garcia et al., 2013).

It is likely that the large increases in agricultural production from Zero Hunger (PRONAF in particular) in the south of Brazil has come at the expense of losses in natural vegetation, as here both the largest losses in natural vegetation cover and increases in daily per capita food production (particularly protein) are found. Within the state of Rio Grande de Sul (which inhabits the Pampa biome) the increases in daily per capita protein production between baseline and endpoint is comprised primarily by soy and milk production increases. Research have found that credit support to livestock activities, or globally traded products with high demand, drives more conversion of natural vegetation than that for crop production (Assunção et al., 2013; Meyfroidt, 2018). Thus, if one knows that certain agricultural activities lends itself more to unintended impacts, interventions could be adapted to avoid this, e.g. to avoid conversion from livestock activities by for instance promoting sustainable and/or more intensive livestock management practices (Cohn et al., 2014), or even conditioning credit or market access on environmental compliance as is done in more northern parts of Brazil (Assunção et al., 2013; Gibbs et al., 2015).

Further research into what drives differences in impact on natural vegetation loss, and thus also what factors motivates positive outcomes for natural vegetation, as found from Zero Hunger and PRONAF in the Atlantic Forest, could also be instrumental in supporting beneficial impact elsewhere. Taking appropriate consideration of non-linear effects of investment (as found by both Zero Hunger and PRONAF) across natural vegetation types is also potentially vital for future implementations of the programme, for as we found, if investment levels are not sensitive to these nuances it might reverse any beneficial increases in natural vegetation cover otherwise gained by the programme.

The importance of local context not only speaks against “one size fits all” approaches to policy, but also warrants caution in blindly expecting a policy proven effective in one country to automatically show similar benefits when rolled out elsewhere. It also illustrates the importance of regular fine-scale monitoring of interventions so that unintended feedbacks and perverse outcomes can be picked up on and modified in time, however this requires frequent and fine-scale data which many developing countries which are now implementing policies similar to Zero Hunger do not have.

4. Conclusion

Brazils’ Zero Hunger social protection policy is globally recognized as a successful programme in reducing poverty, inequality and food insecurity. As such, it is now being rolled out to other developing countries, particularly in Sub-Saharan Africa. Yet no long-term, large-scale programme evaluation which examines the causal links between the Zero Hunger and main sub-programmes and multiple outcomes, intended or unintended, exist. Likewise, little attention has been placed on exploring the impacts for rural communities in particular. To our knowledge, this study is the first to carry out such a holistic evaluation.

Using a systems approach to capture the multi-faceted nature of the programme we focus on rural municipalities across Brazil over a ten year period (2004-2013 and 2000-2010) and find both synergies and trade-offs of the programme. Of particular relevance to the sustainable development goals we find positive impact of Zero Hunger on food production (daily per capita kilocalorie and protein) yet this has not led to equal improvements in food security (child malnutrition and infant mortality) (SDG 2) and our results suggest it has had both positive and negative impacts on the environment (SDG 15 and SDG 13). It has also been less effective in achieving large-scale poverty alleviation (SDG 1) and improvements in well-being (SDG 3), though we we note there are heterogeneous impacts across Brazil.

The heterogeneous impacts we find driven partly by divergent effects from sub-programmes within Zero Hunger, Bolsa Familia and PRONAF in particular, and, we speculate, geographical differences in available infrastructure and institutions which support programme effectiveness are driving these differences. These results have implications for other countries adopting similar policies and development policies in general, and emphasizes the importance of considering local context. It also highlights the importance of regular, holistic and robust programme evaluation.

5. Materials and Methods

Unit of Analysis.

We confine analyses to rural municipalities because Zero Hunger policies implemented in rural and urban areas differ in their implementation, mechanisms, and effectiveness (de Mattos & Bagolin, 2017; Kepple et al., 2014) and because Zero Hunger targets small scale farmers and such rural farmers are vital for national food security – they produce 70% of the food consumed domestically but also suffer disproportionately from food insecurity (Kepple et al., 2014). We use OECD definition of urbanisation, excluding those that have human population densities above 150 inhabitants/km² (OECD, 2011), as the official Brazilian definition overestimates the distribution of urban areas (Rodrigues, 2014). We also exclude municipalities due to missing data and municipality border inconsistencies between baseline and endline (see SI Appendix for more detail), resulting in our main set of analyses covering between 74 and 97% of rural municipalities (3,808 – 4,976 municipalities), which contain between 82% and 97% of Brazil's rural population. For specific model sample sizes see Table S1.

Outcome variables.

Our study period spans either 2000 - 2010 or 2004-2013, depending on data availability for outcome variables. We use eight different variables to cover key dimensions of food production, poverty, food insecurity and health, and environmental degradation: *i) daily per capita kilocalorie production* and *ii) daily per capita protein production*, created by combining macronutrient/food energy values from municipal production of twelve main Brazilian agricultural products (IBGE, 2016); see SI Appendix and Table S4 for more detail, *iii) poverty in the entire population* (IBGE, 2010) and *iv) poverty in the poorer sectors* (Ministerio da Saude, 2015), which combines equally weighted data on health, education, and living standards using the geometric mean following theoretical- and methodological recommendations of Alkire and Foster (2011) and Brazil's official Municipal Human Development Index (MHDI) (Atlas Brazil, 2013) (see Table S5 for details of the index creation, and Fig. S7 for a comparison between our Poverty-Census and Brazil's MHDI), *v) child malnutrition in the poorer sectors* (Ministerio da Saude, 2015) created from data on underweight new-borns and underweight infants (between 12 and 24 months) per 10,000 children weighed, combined by their geometric mean, *vi) infant mortality in the entire population* (IBGE, 2010) and *vii) infant mortality in the poorer sectors* (Ministerio da Saude, 2015), defined as the number of annual infant deaths (children <1 year) per 100,000 live births, and *viii) natural vegetation cover*, created by combining the municipal area of 12 natural vegetation classes from a Brazilian Landsat-derived remote sensing product (MapBiomas, 2017) (see SI Appendix and Table S6 for data compilation process and Table S7 for validation tests).

Treatment variable – Zero Hunger 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 Zero Hunger sub-programmes: PRONAF, PAA, PNAE and Bolsa Familia Bolsa Familia. All four sub-programmes have grown steadily since inception (Fig. S8), and show large spatial variation in terms of investment across Brazil (Fig. S2).

We exclude other components of the programme because they lack data at a municipal level and/or are much more limited in geographical spread. We measure Zero Hunger as the total per capita financial investment allocated to each municipality between 2004 and 2013. Investment values are adjusted for inflation relative to 2013 using Brazil's inflation index IGP-DI, and expressed per R$ 1000 per capita (using population data from IBGE (https://www.ibge.gov.br/)). Given the frequently adopted and complementary approaches of conditional cash transfers (Bolsa Familia) and credit provision (PRONAF) (Devereux, 2016) we also consider the individual impacts of Bolsa Familia and PRONAF. For analyses using outcome variables spanning 2000 to 2010, we measure Zero Hunger as total investment from 2000 to 2010. See SI Appendix for detail on annual programme investment data and our decisions not to incorporate available information on the number of Zero Hunger beneficiaries in our analysis.

Predictor variables.

We control for a range of confounding variables based on their potential influence on both the allocation of Zero Hunger investments to municipalities and our various outcome metrics. These variables include baseline levels for our outcome variables, as well as municipal area, state and ecological biome fixed effects, average slope and elevation, travel time to major population centres, drought incidence, non-PRONAF rural agricultural credit regulated through the Brazilian Central bank, baseline population density, baseline public service investment, and baseline measures of areas dedicated to crop production-, pasture-, small-scale farmers-, and environmental protection (Table S2). A majority of confounding variables are set at baseline year, i.e. at inception of Zero Hunger, to ensure that these variables have not been affected by Zero Hunger. Together with the non-baseline confounding variables which are likely not endogenously determined by investment, these can be used both as predictor variables to control for non-random allocation of investment and as confounding variables when estimating the effect of treatment (investment) on our outcomes. More details about this two-step quasi-experimental approach follows in the next section. When modelling the effect of individual Bolsa Familia and PRONAF programme investment on outcomes we also control for investment in the other Zero Hunger programmes. See Table S2 and SI Appendix for details on each model predictor variable and Table SI for predictor variable inclusion in each CBGPS and outcome model.

Statistical analysis.

We use a two-step quasi-experimental approach (Fong et al. 2017) to estimate the impact of Zero Hunger on food security and the environment. First we use a Covariate Balancing Generalized Propensity Score (CBGPS) method to control for 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 (Stuart & Rubin, 2007). The method builds on previous methods of impact estimation using observational data and uses inverse propensity weighting to create covariate balance. The method is shown to increase the robustness to model misspecification and, as a *generalized propensity score*, is applicable to continuous treatment variables such as our measures of Zero Hunger and sub-programme investment (Fong et al., 2017). We create distinct CBGPS weights for each individual regression model, and use the same predictor variables for the weights as those used in the subsequent regression model (see Table S1). The weights created minimize the correlation between the treatment variable and confounding variables when included in the subsequent regression model, i.e. the second step, and resulted in great reductions in treatment-covariate correlations in all our regression models (Fig. S9). For more details on how the CBGPS weights are created see SI Appendix.

The selection of appropriate modelling framework to estimate the effect of treatment on our outcomes are decided based on each outcomes' error distribution (assessed comparing outcomes to main theoretical distributions using R's "fitdistrplus" package) (see SI Appendix for more detail). Per capita food production, poverty, and natural vegetation are subsequently modelled using robust ordinary least squares (OLS) regressions, based on the a popular robust regression technique called the MM-estimator (Rousseeuw et al., 2015) (see SI Appendix for more detail), after transforming the dependent variables, investment variable, and continuous covariates besides drought incidence, to log base ten. Child malnutrition and infant mortality are modelled using Quasi-Poisson and Negative binomial models given their overdispersed Poisson error structure (overdispersion tested using R's "AER" package). The selection between a Quasi-Poisson and Negative Binomial model is based on the outcomes mean-variance structure (tested by plotting the the quasi-poisson and negative binomial model against the mean-variance of the outcome variable; following Ver Hoef & Boveng (2007)). Also here we transform the investment variable and other continuous covariates, besides the baseline levels for our outcome variables and drought incidence, to log base ten, and achieve great improvements in linear relationships. The robust MM-estimator is not available for Quasi-Poisson and Negative Binomial models. As an alternative robust modelling approach we use another measure of influence (DFBETAS) and 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) (Belsley et al., 2005). For more details regarding DFBETAS see SI Appendix.

State- or biome-investment interaction terms, and/or a quadratic investment terms are retained in the core models when the added term is significant, i.e. 95% confidence intervals (CIs) for the added parameter(s) exclude zero, and when there is improvement in model fit, i.e. when there is an improvement in model AIC value. For the robust models calculated with an MM-estimator AIC is not available, so rather we rely on improvements in adjusted r squared as an appropriate criteria to establish improvement in model fit (Kutner et al., 2005). We acknowledge that a threshold of improvement of at minimum 2 AIC points is often employed to qualify as a real improvement in model fit (Burnham & Anderson, 2004) and note that our model selections based on AIC all had AIC improvements above that threshold. A state-investment interaction was retained for all per capita food production- and poverty-Census models, as well as for PRONAF and poverty-, and Bolsa Familia and child malnutrition-SIAB models. A biome-investment interaction was retained for Zero Hunger- and PRONAF and natural vegetation cover models. In six cases a state or biome-investment interaction included interaction coefficients with 95% CIs which excluded zero, however, adding them did not result in improvements in model fit. This could happen due to random chance or overfitting and as such these terms were not retained in the final model. For more information see SI Appendix. A quadratic investment term was retained for the Zero Hunger and poverty-Census model, and Zero Hunger- and PRONAF and natural vegetation cover models. Table S1 lists all parameters in each core model, whilst Table 2 shows all core model investment parameters and each models explanatory power.

When interpreting the investment parameters in Table 2, note that because the state and biome factor variables are coded using deviation coding (also known as effect coding), all state and biome interaction effects are expressed relative to the main investment parameters, which express the average effect across Brazil (often referred to as the grand average effect). As the measure of model explanatory power we use model r squared values (for the robust OLS regression models) and McFadden pseudo r squared values (for the Negative Binomial models). No equivalent measure is available for Quasi-Poisson models.

We use the resultant regression equation from the core models to quantify the impact of investment by calculating the predicted value of our outcome variables under two 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 and avoid predicting at the very extremes of our data), ii) the actual investment received in each municipality, and iii) spatially uniform investment levels equating to the 25th, 50th and 95th 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). We also generate maps of relative impact under a spatially uniform median investment level (defined as percentage change in predicted outcome between a negligible and a 50th percentile investment level) (Fig. S1), this due to the substantial variation in the amount of Zero Hunger investment received by municipalities (Fig. S2). This approach helps to visualise spatial variation in the effectiveness of investment whilst accounting for heterogeneity in the magnitude of investment. When a specific state or biome interaction effect is significantly different to the grand average effect we highlight this by thick black borders. Lastly, to assess the non-linear effect of investment in outcomes modelled with a quadratic investment term, we calculate the percentage change in outcome variables between a negligible investment scenario and when each municipality received a much lower amount of investment (defined as the 25th percentile investment value), when they received a median investment amount, and a much higher amount of investment (defined as the 95th percentile investment value). Then we plot the non-linear slopes (Fig. S3-6).

Robustness checks.

We validate the results of our core analyses using a series of robustness checks. First we re-run each model excluding municipalities for which there was uncertainty regarding data quality, defined as: i) municipalities larger than 10,000 km^2 as larger municipalities are more likely to have unrepresentative socio-economic data (Gregorio et al., 2005) used in all models as either outcome variables and/or confounding variables; ii) for models using SIAB data (child malnutrition, infant mortality and poverty) municipalities that did not meet the quality criteria set by Brazil's Ministry of Health (Ministerio da Saude, 2003), 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. A 5% threshold of cloud cover we consider as an appropriately stringent threshold. See Table S8 for municipalities excluded in these robustness models, and SI Appendix and Table S3 for a comparison of the robustness models with core results.

Second, we assess the presence of spatial autocorrelation, i.e. lack of independence among observations due to neighbourhood physical or structural factors (Legendre, 1993), given that a lack of independence violates the assumption of independence in classical statistics and can bias our results (Legendre, 1993). A spatial autocorrelation test is also useful to assess whether after controlling for confounders, the spatial pattern of our treatment allocations and outcomes are close to random, i.e. spatially-determined unmeasured confounders are unlikely (Paciorek, 2010). We test for spatial autocorrelation by running two-sided Moran's I tests on all core model residuals as well as model residuals from the covariate-balancing stage (CBGPS). We create two neighbourhood matrices (one based on touching municipality borders and one based on distance) to account for both structural and physical patterns (see SI Appendix for more detail) and consider presence of significant spatial-autocorrelation when Morans I values are far from 0 and corresponding p-values are below 0.05 (Griffith, 2009). See SI Appendix for spatial autocorrelation results.

Third, we look for presence of endogeneity, i.e. dependence between the model error term and an independent variable of interest. Presence of unmeasured confounders is a main cause of endogeneity and often tested through a Hausman test (Guo & Fraser, 2015). Carrying out this test is, however, not always feasible (Guo & Fraser, 2015) (see SI Appendix for more detail), and thus we revert to a semi-formal test for endogeneity and assess whether the error term (model residuals) and our main variable of interest (investment variable) are correlated, based on Spearmans' rho correlations.

6. References.

Agência IBASE. (2008). Repercussões do programa Bolsa Família na segurança alimentar e nutricional das Familias beneficiadas. Rio de Janeiro.

Alix-garcia, J., Mcintosh, C., Sims, K. R. E., & Welch, J. R. (2013). The Ecological Footprint of Poverty Allevation: Evidence from Mexico's Oportunidades Program. *The Review of Economics and Statistics*, *95*(2), 417–435.

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, *95*(7–8), 476–487. http://doi.org/10.1016/j.jpubeco.2010.11.006

Araújo, F. R. de, Araújo, M. A. D. de, Souza, F. J. V. de, Gurgel, I. L. P., & Gomes, A. C. C. (2018). Distribuição Espacial do Desempenho do Programa Bolsa Família: Um Estudo à Luz do IGD-M. *Revista de Ciencias Sociais, Rio de Janeiro*, *61*(3), 773–806.

Assunção, J., Gandour, C., Rocha, R., & Rocha, R. (2013). *Does Credit Affect Deforestation? Evidence from a Rural Credit Policy in the Brazilian Amazon*. Retrieved from http://climatepolicyinitiative.org/wp-content/uploads/2013/01/Does-Credit-Affect-Deforestation-Evidence-from-a-Rural-Credit-Policy-in-the-Brazilian-Amazon-Technical-Paper-English.pdf

Atlas Brazil. (2013). The MHDI: Atlas of Human Development in Brazil. Retrieved November 3, 2015, from http://www.atlasbrasil.org.br/2013/en/o_atlas/idhm/

Barlow, J., Gardner, T. A., Araujo, I. S., Avila-Pires, T. C., Bonaldo, A. B., Costa, J. E., … Peres, C. A. (2007). Quantifying the biodiversity value of tropical primary, secondary, and plantation forests. *Proceedings of the National Academy of Sciences*, *104*(47), 18555–18560. http://doi.org/10.1073/pnas.0703333104

Barretto, A. G. O. P., Berndes, G., Sparovek, G., & Wirsenius, S. (2013). Agricultural intensification in Brazil and its effects on land-use patterns: an analysis of the 1975 – 2006 period. *Global Change Biology*, *19*, 1804–1815. http://doi.org/10.1111/gcb.12174

Barrientos, A. (2012). Social Transfers and Growth : What Do We Know ? What Do We Need to Find Out ? *World Development*, *40*(1), 11–20. http://doi.org/10.1016/j.worlddev.2011.05.012

Barrientos, A. (2017). Design and rural context in antipoverty transfers: Implications for programme outcomes. *Global Food Security*, *12*(March 2016), 103–108. http://doi.org/10.1016/j.gfs.2016.09.002

Belsley, D. A., Kuh, E., & Welsch, R. E. (2005). *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. John Wiley & Sons.

Benton, T. (2016). The many faces of food security. *International Affairs*, *92*(6), 1505–1515. http://doi.org/10.1111/1468-2346.12755

Burnham, K. P., & Anderson, D. R. (2004). Multimodel Inference: Understanding AIC and BIC in

Model Selection. *Sociological Methods Research, 33*. http://doi.org/10.1177/0049124104268644

Castaneda, R. (2012). *Zero Hunger: The Brazilian experience*. Rome. Retrieved from http://www.un.org/en/zerohunger/challenge.shtml

CFS. (2012). *Coming to terms with terminology: Food security, nutrition security, food security and nutrition, food and nutrition security*.

Coates, J. (2013). Build it back better: Deconstructing food security for improved measurement and action. *Global Food Security*, *2*(3), 188–194. http://doi.org/10.1016/j.gfs.2013.05.002

Cohn, A. S., Mosnier, A., Havlík, P., Valin, H., Herrero, M., Schmid, E., … Obersteiner, M. (2014). Cattle ranching intensification in Brazil can reduce global greenhouse gas emissions by sparing land from deforestation. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(20), 7236–41. http://doi.org/10.1073/pnas.1307163111

de Mattos, E. J., & Bagolin, I. P. (2017). Reducing Poverty and Food Insecurity in Rural Brazil: the Impact of the Zero Hunger Program. *EuroChoices*, *16*(1), 43–49. http://doi.org/10.1111/1746-692X.12150

Devereux, S. (2016). Social protection for enhanced food security in sub-Saharan Africa. *Food Policy*, *60*, 52–62. http://doi.org/10.1016/j.foodpol.2015.03.009

Doretto, M., & Michellon, E. (2007). Avaliação dos Impactos Econômicos, Sociais e Culturais do Programa de Aquisição de Alimentos no Paraná, (43), 107–138. Retrieved from http://www.iapar.pr.gov.br/arquivos/File/zip_pdf/aval_impact_econo.pdf

Dorward, A. R., Kirsten, J. F., Omamo, S. W., Poulton, C., & Vink, N. (2009). Institutions and the agricultural development challenge in Africa. In *Institutional economics perspective on African agricultural development* (pp. 1–34). Washington DC: IFPRI. Retrieved from http://www.slideshare.net/ludymae/chapter-6theoretical-conceptual-framework

Edwards, D. P., Massam, M. R., Haugaasen, T., & Gilroy, J. J. (2017). Tropical secondary forest regeneration conserves high levels of avian phylogenetic diversity. *Biological Conservation*, *209*, 432–439. http://doi.org/10.1016/j.biocon.2017.03.006

Eusebio, G. dos S., Maia, A. G., & Silveira, R. L. F. da. (2016). Impact of microcredit on small-farm agricultural production: evidence from Brazil. In *Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, MA, July 31-August 02*.

FAO, IFAD, UNICEF, WFP, & WHO. (2017). *The State of Food Security and Nutrition in the World. Building resilience for peace and food security*. Rome.

Fong, C., Hazlett, C., & Imai, K. (2017). Covariate Balancing Propensity Score for a Continuous Treatment : Application to the Efficacy of Political. *Forthcoming in Annals of Applied Statistics*.

Fraundorfer, M. (2013). Zero hunger for the world: Brazil´s global diffusion of its Zero Hunger strategy. *Austral: Brazilian Journal of Strategy & International Relations*, *2*(4), 91–116.

Gibbs, H. K., Rausch, L., Munger, J., Schelly, I., Morton, D. C., Noojipady, P., … Cerrado, E. (2015).

Brazil's Soy Moratorium. *Science - Policy Forum: Environment and Development*, *347*(6220), 377–378. http://doi.org/10.1126/science.aaa0181

Grebmer, K., Ringler, C., Rosegrant, M. W., Olofinbiyi, T., Wiesmann, D., Fritschel, H., … Rahall, J. (2012). *Global Hunger Index: The challenge of hunger: ensuring sustainable food security under land, water, and energy stresses*. *IFPRI - Issue Brief*. Bonn/ Washington, DC/Dublin.

Griffith, D. A. (2009). Methods: spatial autocorrelation. In R. Kitchin & N. Thrift (Eds.), *International Encyclopedia of Human Geography* (pp. 396–402). NY: Elsevier.

Guo, S., & Fraser, M. W. (2015). Counterfactual Framework and Assumptions. In *Propensity Score Analysis: statistical methods and applications* (p. 448). SAGE Publications Ltd.

Hall, A. (2008). Brazil's Bolsa Familia : A Double-Edged Sword? *Development and Change*, *39*(5), 799–822.

Helfand, S. M., Moreira, A. R. B., & Jr., E. W. B. (2015). *Agricultural Productivity and Family Farms in Brazil : Creating Opportunities and Closing Gaps*.

Hoef, J. M. Ver, & Boveng, P. L. (2007). Quasi-Poisson vs . Negative Binomial Regression : How Should We Model Overdispersed Count Data: *Ecology*, *88*(11), 2766–2772.

IBGE. (2010). Censo Demografico. Retrieved March 27, 2018, from https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2010/inicial

IBGE. (2016). Produção Agrícola Municipal. Retrieved May 1, 2016, from http://www.sidra.ibge.gov.br/bda/pesquisas/pam/

Ingram, J. (2011). A food systems approach to researching food security and its interactions with global environmental change. *Food Security*, *3*(4), 417–431. http://doi.org/10.1007/s12571-011-0149-9

Joly, C. ., Metzger, J. P., & Tabarelli, M. (2014). Experiences from the Brazilian Atlantic Forest : ecological findings and conservation initiatives. *New Phytologist*, *204*(3), 459–473.

Kepple, A. W., Carolina, A., Silva, F., & Fernandes, E. A. (2014). *The state of food and nutrition security in Brazil: A multi-dimensional portrait*. Brasilia.

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). *Applied Linear Statistical Models* (Fifth Edit). McGraw-Hill/Irwin.

Leão, M. M., & Maluf, R. S. (2013). *Effective public policies and active citizenship: Brazil´s experience of building a Food and Nutrition Security System*. Brasilia.

Legendre, P. (1993). Spatial Autocorrelation : Trouble or New Paradigm? *Ecology*, *74*(6), 1659–1673.

Liao, C., & Brown, D. G. (2018). Assessments of synergistic outcomes from sustainable intensification of agriculture need to include smallholder livelihoods with food production and ecosystem services. *Current Opinion in Environmental Sustainability*, *32*(April), 53–59. http://doi.org/10.1016/j.cosust.2018.04.013

Loos, J., Abson, D. J., Chappell, M. J., Hanspach, J., Mikulcak, F., Tichit, M., & Fischer, J. (2014). Putting meaning back into "sustainable intensification." *Frontiers in Ecology and the*

Environment, *12*(6), 356–361. http://doi.org/10.1890/130157

MapBiomas. (2017). Coleções MAPBIOMAS. Retrieved August 20, 2017, from http://mapbiomas.org/pages/database/mapbiomas_collection

Mercure, J., Paim, M. A., Bocquillon, P., Lindner, S., Salas, P., Martinelli, P., … Vinuales, J. E. (2019). System complexity and policy integration challenges : The Brazilian Energy- Water-Food Nexus. *Renewable and Sustainable Energy Reviews*, *105*(February), 230–243. http://doi.org/10.1016/j.rser.2019.01.045

Meyfroidt, P. (2018). Trade-offs between environment and livelihoods: Bridging the global land use and food security discussions. *Global Food Security*, *16*, 9–16. http://doi.org/10.1016/j.gfs.2017.08.001

Ministerio da Saude. (2003). *Sistema de Informação da Atenção Básica SIAB Indicadores 2002*.

Ministerio da Saude. (2015). SIAB: Sistema de Informação de Atenção Básica. Retrieved March 18, 2015, from http://www2.datasus.gov.br/DATASUS/index.php?area=0205

MMA. (2007). *Priority Areas for the Conservation , Sustainable Use and Benefit Sharing of Brazilian Biological Diversity*. Brasilia: Ministry of the Environment.

Myers, N., Mittermeier, R. A., Mittermeier, C. G., Fonseca, G. A. B., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, *403*, 853–858.

Nazareno, A. G., & Laurance, W. F. (2015). Brazils drought: Beware deforestation. *Science*, (July).

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., … Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, *520*(7545), 45–50. http://doi.org/10.1038/nature14324

OECD. (2011). OECD regional typology.

Oldekop, J. a., Chappell, M. J., Peixoto, F. E. B., Paglia, A. P., do Prado Rodrigues, M. S., & Evans, K. L. (2015). Linking Brazil’s food security policies to agricultural change. *Food Security*. http://doi.org/10.1007/s12571-015-0475-4

Osorio, R. G., Souza, P. H. G. F. de, Soares, S. S. D., & Oliveira, L. F. B. de. (2011). *Perfil da pobreza no Brasil e sua evolução no período 2004-2009*.

Overbeck, G. E., Müller, S. C., Fidelis, A., Pfadenhauer, J., Pillar, V. D., Blanco, C. C., … Forneck, E. D. (2007). Brazil’s neglected biome: The South Brazilian Campos. *Perspectives in Plant Ecology, Evolution and Systematics*, *9*(2), 101–116. http://doi.org/10.1016/j.ppees.2007.07.005

Paciorek, C. J. (2010). The Importance of Scale for Spatial-Confounding Bias and Precision of Spatial Regression Estimators. *Statistical Science*, *25*(1), 107–125. http://doi.org/10.1214/10-STS326

Paes-Sousa, R., Santos, L. M. P., & Miazaki, É. S. (2011). Effects of a conditional cash transfer programme on child nutrition in Brazil. *Bulletin of the World Health Organization*, *89*(7), 496–503. http://doi.org/10.2471/BLT.10.084202

Pinto, S., Melo, F., Tabarelli, M., Padovesi, A., Mesquita, C., de Mattos Scaramuzza, C., … Brancalion, P. (2014). Governing and Delivering a Biome-Wide Restoration Initiative: The Case of Atlantic Forest Restoration Pact in Brazil. *Forests*, *5*(9), 2212–2229. http://doi.org/10.3390/f5092212

Piperata, B. A., McSweeney, K., & Murrieta, R. S. (2016). Conditional Cash Transfers, Food Security, and Health: Biocultural Insights for Poverty-Alleviation Policy from the Brazilian Amazon. *Current Anthropology*, *57*(6), 806–826. http://doi.org/10.1086/688912

Rasella, D., Aquino, R., & Barreto, M. L. (2010). 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. http://doi.org/10.1186/1471-2458-10-380

Rasella, D., Aquino, R., Santos, C. a T., Paes-Sousa, R., & Barreto, M. L. (2013). Effect of a conditional cash transfer programme on childhood mortality: a nationwide analysis of Brazilian municipalities. *Lancet*, *382*(9886), 57–64. http://doi.org/10.1016/S0140-6736(13)60715-1

Rocha, C., Burlandy, L., & Maluf, R. (2012). Small farms and sustainable rural development for food security : The Brazilian experience. *Development Southern Africa*, *29*(4).

Rodrigues, J. F. (2014). O rural e o urbano no Brasil : uma proposta de metodologia de classificação dos municípios. *Analise Social*, *211*(49), 431–456.

Rousseeuw, P., Croux, C., Todorov, V., Ruckstuhl, A., Salibian-barrera, M., Verbeke, T., … Maechler, M. M. (2015). Package 'robustbase.' *R Topics*.

Samberg, L. H., Gerber, J. S., Ramankutty, N., Herrero, M., & West, P. C. (2016). Subnational distribution of average farm size and smallholder contributions to global food production. *Environmental Research Letters*, *11*(12), 1–11. http://doi.org/10.1088/1748-9326/11/12/124010

Sayer, J., Sunderland, T., Ghazoul, J., Pfund, J.-L., Sheil, D., Meijaard, E., … Buck, L. E. (2013). Ten principles for a landscape approach to reconciling agriculture, conservation, and other competing land uses. *Proceedings of the National Academy of Sciences*, *110*(21), 8349–8356. http://doi.org/10.1073/pnas.1210595110

Schüring, E. (2010). *Conditions, conditionality, conditionalities , responsibilities – finding common ground*.

Sidaner, E., Balaban, D., & Burlandy, L. (2013). The Brazilian school feeding programme: an example of an integrated programme in support of food and nutrition security. *Public Health Nutrition*, *16*(6), 989–94. http://doi.org/10.1017/S1368980012005101

Silva, J. G. da, Grossi, M. E. Del, & França, C. G. de. (2011). *The Fome Zero (Zero Hunger) Program: The brazilian experience*. (J. G. da Silva, M. E. Del Grossi, & C. G. de França, Eds.). Brasilia.

Smith, L. C., & Haddad, L. (2015). Reducing Child Undernutrition: Past Drivers and Priorities for the Post-MDG Era. *World Development*, *68*(1), 180–204. http://doi.org/10.1016/j.worlddev.2014.11.014

Soares, F. V., Ribas, R. P., & Osorio, R. G. (2010). Evaluating the Impact of Brazil's Bolsa Familia: Cash transfer programs in comparative perspective, *45*(2), 173–190.

Stuart, E. A., & Rubin, D. B. (2007). Best practices in quasi-experimental designs: Matching methods for causal inference (pp. 155–176).

Thorkildsen, K. (2014). Social-Ecological Changes in a Quilombola Community in the Atlantic Forest of Southeastern Brazil. *Human Ecology*. http://doi.org/10.1007/s10745-014-9691-3

Todd, J. E., Winters, P. C., & Hertz, T. (2010). Conditional cash transfers and agricultural production: Lessons from the oportunidades experience in Mexico. *Journal of Development Studies*, *46*(1), 39–67. http://doi.org/10.1080/00220380903197945

Tubiello, F. N., Salvatore, M., Ferrara, A. F., House, J., Federici, S., Rossi, S., … Smith, P. (2015). The Contribution of Agriculture, Forestry and other Land Use activities to Global Warming, 1990-2012. *Global Change Biology*, *21*(7), 2655–2660. http://doi.org/10.1111/gcb.12865

Vieira, I. (2015). *Policies for Rural Development : an Analysis Focusing on the North and Northeast Regions of Brazil*. Brasilia.

7. Supplementary Information

7.1. SI Text

Unit of Analysis. We compile data at the municipality level, i.e. Brazil's lowest administrative unit. In addition to urban municipalities we also exclude municipalities due to missing data, including cases where certain covariate information lacked correct municipality ID, preventing us from merging them with the larger dataset. 41 municipalities were split into two or more municipalities during our study period. For these we use the municipality boundaries at the start of the study period and recalculate variables for this area by summing together the raw municipality values and then calculating new combined rate-, percentage-, and per capita values. When raw values were not available we averaged data for the newly created municipalities using weighted means (by municipality area for average slope, average elevation, and drought incidence; and by population size for infant mortality- and life expectancy for the overall population). For municipal remoteness we use a normal (non-weighted) mean given that any influence of size is already accounted for in the remoteness variable. 4-45 additional municipalities had to be excluded, however, because the change in municipality borders, i.e. multiple municipalities merged to create single municipalities, were such that 2010 or 2013 (endpoint) values could not be accurately assigned baseline boundaries.

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) (Remans et al., 2014). Both measures are based on annual municipal agricultural production data from the national statistics office (IBGE, 2016). 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 (FBA/USP, 2008; USDA, 2008). Wee use the average between the two sources when product values from both are available (Table S4). We then convert to daily per capita values based on the municipality's population size in the focal year (using data from the Brazilian Institute of Geography and Statistics (IBGE) (https://www.ibge.gov.br/)). The agricultural data does not include subsistence food production. However, with the shift towards a more modernized market oriented agriculture such production is small, and declining, relative to overall production (Silva, Grossi, & França, 2011).

Poverty. We use data from the 2000 and 2010 demographic census to generate a multidimensional poverty index (MPI), which we refer to as Poverty-Census, based on the recommendations of Alkire and Foster (2011). Our measure combines equally weighted data on health, education, and living standards. Because household-level data are not available as part of the census micro-data, we use the geometric mean to generate our combined poverty measure. This method follows the method used to calculate Brazil's official Municipal Human Development Index (MHDI) (Atlas Brazil, 2013), which is also 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 standard given its more direct measure of deprivation of capabilities in line with the rationale of the MPI (Alkire & Foster, 2011), and within 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 Zero Hunger programmes (Silva et al., 2011). See Fig. S7 for information on relationships between the 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 (Alkire and Foster, 2011), our index provides a strong indicator of temporal change in poverty. In addition, we use data from the Brazilian National Primary Information System (SIAB) for 2004 and 2013 (Ministerio da Saude, 2015), which we refer to as Poverty-SIAB to assess poverty change in the poorer sectors of society. SIAB contains vital information for all families targeted by The Family Health Programme. This programme is the national decentralised primary health care programme aimed at providing health care coverage especially to deprived areas (Rasella et al., 2010), and as such can be said to contain information for the poorer sectors of society. The Poverty-SIAB metric combines equally weighted data on health, education, and living standards but uses slightly different variables for each dimension than those used by Poverty-SIAB (see Table S5) and the two metrics are thus not directly comparable.

Malnutrition and mortality. We use child malnutrition and infant mortality as metrics of food insecurity (Young & Jaspars, 2009). 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 infants (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 (Xavier et al., 2015). 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* (MapBiomas, 2017). 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 S6). We calculate area of natural vegetation in each municipality and validate these estimates by comparison with an alternative dataset, i.e. Terra Class Amazon and Cerrado, PMDBBS Caatinga and Cerrado, and SOS Atlantic Forest (Table S7). 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 variable - Zero Hunger policy implementation. Information on the number of beneficiaries is publicly available for some Zero Hunger sub-programmes, but this variable is not defined in a consistent way as one beneficiary could represent one individual farmer, one co-operative that contains multiple farmers (but an unknown number) 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 Zero Hunger programme or its sub-programmes. A financial value capturing Zero Hunger programme investment is thus more appropriate.

The Zero Hunger programme was officially launched in 2003. However, we focus the majority of our analysis from 2004 onwards because investment levels in the programme's first year were small (Junior, 2009; UNDP-IPC, 2013) and major changes to Zero Hunger's largest sub-programme, Bolsa Familia, were implemented in 2004 (Mourao, Ferreira, & Jesus, 2009). Furthermore, due to data availability, we only include investment on PAA from 2006 onwards. However, investment in this sub-programme prior to 2006 is minimal (Fig. S4). For analyses using outcome variables spanning 2000 to 2010, we try to match investment to the same time frame and as much as possible measure Zero Hunger as total investment from 2000 to 2010. This means it includes investment values for PNAE and PRONAF from 2000 as these two sub-programmes were operational prior to Zero Hunger's inception in 2003.

Predictor variables.

i) Total municipal area. Administrative area size has been found to significantly influence social and environmental outcomes in previous impact estimation studies (Andam et al., 2008).

ii) States. States in Brazil have substantial decision-making power, heterogeneous economies, and receive different amounts of federal financial support (Silva et al., 2011).

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 (MMA, 2007), with significant implications for agricultural production and rural livelihoods. We assign a specific biome to each municipality if ≥ 80% of a municipality's area falls within a biome (IBGE & MMA, 2004). Municipalities with less than 80% of their area within one biome (n=253) were assigned one of seven transition categories. We do so to account for possible different environmental conditions in transition areas (Banks-Leite & Ewers, 2009). Three of these transition categories (Cerrado/Pantanal, Pantanal/Amazon, Atlantic forest/Pampa) occurred in less than 20 municipalities, which adversely affected model convergence in the natural vegetation models. Thus for the natural vegetation models we used a threshold of >50% of municipality area when assigning a specific biome to each municipality, resulting in each municipality falling within one of Brazil's six biomes.

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 (World Bank, 2008). We measure baseline population density using population estimates and municipal area data from IBGE (https://www.ibge.gov.br/).

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 (IBGE, 2015). We deflate these values relative to 2013, and express them per R$ 1000 per capita using population data from IBGE.

vi – vii) Land use. To account for the agricultural sectors' likely influence on our outcome variables we control for *Area under crop production*- (IBGE, 2016) and *Area under pasture at baseline* (IBGE, 2006). Area under crop production at baseline refer to year 2000 and 2004 for the respective 2000-2010 and 2004-2013 models, while area under pasture is taken from 2006, a few years after our baselines. Prior agricultural census data were not available, and we chose to use the 2006 census data rather than MapBiomas' 2000/2004 pasture measure because of the presence of uncertainty in the MapBiomas dataset regarding what is pasture area (as opposed to crop area), exemplified by their inclusion of an "agriculture or pasture" category (note they use the term agriculture to refer to crop area) which even in the newly released collection 3, cover 24% of total farm area identified for Brazil (www.mapbiomas.org/stats, accessed February, 2019). We also control for municipal presence of small-scale farms and include a measure of total farm *area by farms <50 ha at baseline* (IBGE, 2006), again only available for 2006. We adopt this threshold rather than the standard 2 hectare threshold because it is far more appropriate for the reality of small-scale family farms in Brazil, and because the 2 hectare definition has been pointed out to distort the reality of smallholder agriculture many places around the world and particularly in Latin-America (Berdegué & Fuentealba, 2011).

ix) 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 (2014), and incorporate information on land cover (European Space Agency, 2014), transportation routes (FGM, 2013), and slope and elevation (Aster GDEM, 2011), to arrive at the fastest travel time from each municipality centroid to a major city, following Oldekop et al. (2018). We use cities with at least 50,000 inhabitants as this is where large markets and adequate health services can be found (Guedes et al., 2012; Moreira & Escorel, 2009). Note that these travel times are highly correlated to travel times to both smaller and larger cities of 10,000, 150,000, 250,000 inhabitants, and state capitals (r=0.73-0.94).

x) Drought intensity. Drought is likely to have adversely impacted our baseline and current food security measures (Glickhouse, 2015; Sietz et al., 2006; Stauffer, 2013). We calculate an average municipal drought index using the global Standardised Precipitation-Evapotranspiration Index (SPEI). This is a continuous index ranging from < -2 (extremely dry) to > 2 (extremely wet), based on the standard deviation from the average climatic balance, i.e. precipitation minus evapotranspiration potential, between 1901-2013 (Beguería & Vicente Serrano, 2014). We use the average drought for three years spanning our baseline and endpoint years respectively to create cumulative drought indices for these two time points. We then subtracted 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.

xi) Agricultural credit. We also consider possible legacy effects of other farming assistance programmes. We control for the amount of *total rural agricultural credit* (that is not PRONAF credit) allocated to each municipality per capita regulated by the Brazilian Central Bank (Banco Central do Brasil, 2017), on the basis that rural credit has been shown to be associated to various dimensions of food security (Burgess & Pande, 2005; Rosenzweig & Wolpin, 1993) and land use change (Assunção et al., 2013).

xii-xiii) *Slope and elevation*. We calculate and control for average slope (in degrees) and average elevation (in meter) per municipality using the global digital elevation model v2 (Aster GDEM, 2011), on the basis that both contribute to agro-ecological conditions which affect food production, natural vegetation cover and livelihoods (Fischer et al., 2002).

xiv) Conservation policies. We control for *Area under protection (at baseline)* when we model the effect of Zero Hunger investment on natural vegetation cover, based on previous studies showing the influence of protection on deforestation (Andam et al., 2008; Soares-Filho et al., 2010). Boundaries of all designated protected areas, i.e. all strictly protected-, sustainable use- 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).

Covariate Balancing Generalized Propensity Score (CBGPS). The CBGPS method by Fong et al. (Fong et al., 2017) offers both a parametric and non-parametric calculation to generate covariate balancing weights. We use both approaches to calculate covariate balancing weights and retain the weights which resulted in the lowest average and/or max correlation. We create distinct weights for each individual regression model, and use the same predictor variables for the weights as those used in the subsequent regression model (see Table S1). For example, the weights used in the model to estimate the effect of total per capita Zero Hunger investment on daily per capita kilocalorie production (row 1 Table S1) have been created through the CBGPS method by specifying Zero Hunger investment as the function of the confounding variables listed in row 1 Table S1). The weights included in subsequent regression models resulted in an average treatment-covariate correlation for each model of 0.06 (compared to an original average treatment-covariate correlation of 0.13) (Fig. S9).

Selecting modelling frameworks. We decide on appropriate model frameworks for each outcome variable by fitting main theoretical distributions (normal, log-normal, Poisson and Negative binomial) to each outcome using R's "fitdistrplus" package. Food production, poverty and natural vegetation are subsequently modelled using ordinary least squares (OLS) regressions after transforming the dependent variables, investment variable, and continuous covariates besides drought incidence, to log base ten, resulting in great improvements in linear relationships and Gaussian distributions of subsequent model residuals. For the variables that include zero we add a constant of half of the minimum value before logging. Model diagnostics reveal presence of outliers. We thus use R's "robustbase" package which offer the MM-estimator – a popular robust regression technique with a high statistical efficiency and high ability to withstand multiple outliers without breaking down (Croux et al., 2003) – and heteroscedasticity and autocorrelation consistent standard errors (Rousseeuw et al., 2015).

Child malnutrition and infant mortality were more appropriately modelled using Quasi-Poisson and Negative binomial models given their overdispersed Poisson error structure. Overdispersion was quantified using the Test for overdispersion found in R's AER package, and ranged 33 – 74,289. We transform the investment variable and continuous covariates to log base ten, besides the baseline levels for our outcome variables and drought incidence, and achieve great improvements in linear relationships. The selection between a Quasi-Poisson and Negative Binomial we based on the outcomes mean-variance structure (Ver Hoef & Boveng, 2007), resulting in Infant mortality-Census being modelled using a Negative Binomial model, and Infant mortality- and Child malnutrition-SIAB using Quasi-Poisson models. A robust MM-estimator cannot be calculated for Quasi-Poisson and Negative Binomial models. We thus follow the suggestion from Coxe et al. (2009) and use another measure of influence, DFBETAS, to conduct analyses that are equivalent to robust regressions. DFBETAS can be calculated for each regression coefficient for each case to "assess the number of standard deviations by which an individual changes each regression coefficient" (Coxe et al., 2009, p.130). 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) (Belsley et al., 2005), given that these points may be producing or obscuring significant effects of investment that are present but not seen when the case is included (Coxe et al., 2009).

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), lack of independence between the treatment variable and error term (endogeneity), and presence of unmeasured confounders.

Data Quality. The number of municipalities excluded due to possible quality issues range from 98 to 1,847 depending on the model (Table S8). Exclusions based on municipality size, employed to all models, affect to a large degree northern and centre-western states (excluding from 3% to 61% of municipalities in a state). Exclusions based on excessive cloud cover, employed to the natural vegetation cover models, affect selected states situated in the north or north east, here reducing the state sample sizes between 1 and 75%. The largest municipal exclusions happen in models using SIAB data (poverty-, child malnutrition-, and infant mortality in the poorer sectors of society) where municipalities with inconsistent and possibly erroneous data are excluded based on criteria set by the Ministry of Health (Ministerio da Saude, 2003). Regions are affected fairly equally by exclusions, with average municipalities excluded within states per region ranging 35-49% (100% of municipalities in Amapa excluded).

The quality control check generate qualitatively identical results for models of per capita protein production and infant mortality-Census. Minor inconsistencies are found between the quality control and core models for some daily per capita kilocalorie production-, poverty-Census and SIAB-, infant mortality-SIAB and natural vegetation models. First, in the quality models the overall effects of Bolsa Familia- and PRONAF investment on daily per capita kilocalorie production are no longer significantly associated with change in per capita production (see Table 1 for core results and Table S3 for robustness). However, some states still show significant effect of investment (10 states significantly affected by Bolsa Familia and 6 from PRONAF investment) and the direction of effect is the same, though magnitude varies slightly. The increase in variation around the investment parameters is likely why overall significant effect disappears, and we note the standard error around the overall main investment parameter estimates are noticeably larger in the robustness models (standard errors relative to parameter estimates in the Bolsa Familia and PRONAF quality control models are 3.2 and 0.8 whilst in the core models they both are 0.4, respectively). This could be caused by selected states having substantially smaller sample sizes leading to unstable and/or less precise estimates (e.g. in the Amazon state (north) only 39% of the core sample is included in the quality model). For the PRONAF and poverty in the poorer sectors (poverty-SIAB) and Bolsa Familia and natural vegetation cover models, the significance of effect of investment disappears. However, for Bolsa Familia it remains close to the threshold of statistical significance. Qualitatively speaking, however, the difference between the core and quality models are minor as the core models showed only negligible effects of investment.

As a second minor inconsistency, the effects recorded in the state of Para (north) are noticeably different between core and quality models and changes both in magnitude and direction of effect in the Bolsa Familia and daily per capita kilocalorie production-, Zero Hunger and per capita protein production-, and PRONAF and poverty in the overall population (poverty-Census) models. Though only 21% of the municipalities in Para are excluded in the quality sample, the remaining municipalities represent only 25% of the original geographical area, and situated almost exclusively in the western part of the state. As such, it is plausible that both models accurately estimates the effect of investment for the sampled municipalities.

The poverty-Census models show two further inconsistencies. First, in the Zero Hunger quality model the non-linear effect of investment is more pronounced and show more beneficial effects of higher levels of investment (at the 95th percentile investment level poverty is now reduced by 2% as opposed to almost reaching reduction). Thus, the quality model only further supports the conclusion that in order for Zero Hunger to be effective at poverty reduction, higher investment levels are needed. The quality model, however, suffers from more uncertainty around certain state-investment estimates, and though the direction and magnitude of effects are the same, these effects are no longer significantly different to the overall (grand) effect and the 95% CIs of the interaction estimates include zero. Second, the Bolsa Familia poverty-Census quality model shows evidence of a non-linear effect of investment, however upon close examination we see that this non-linear effect closely resembles the slope of the linear effect recorded in the core model (Fig. S6). Importantly it does show that given actual investment levels the overall effect of Bolsa Familia investment is slightly beneficial (2% reduction in poverty overall as opposed to a 24% overall increase in the core model) and in particular states in the north-east region of Brazil show average poverty alleviation effects. The core model also revealed a handful of north-eastern states with non significant poverty alleviation trends (Fig. 1).

As a final minor inconsistency, the significance of effect of total PRONAF investment on infant mortality in the poorer sectors of society (SIAB), and the effect of total PRONAF investment on natural vegetation cover changes between the core and quality model. A non-significant effect of PRONAF investment on infant mortality in the poorer sectors of society (SIAB) in the core model turns into an effect of investment in three states in the quality control model (Rondonia, Parana and Rio Grande do Sul). One could assume that excluding unreliable municipality data (as in the quality model) would make it easier for the model to pick up on true effects and there is an effect from PRONAF investment in these three states. On the other hand, because the amount of municipalities deleted in these states are substantial (42 – 62% of the core state samples) estimating true effects might be more difficult (unstable estimates). A third explanation is that the effects are accurately estimated for the sample in each model. Looking at the effect sizes of these three states we do question their plausibility (effect sizes ranging from -99% to +615%), particularly since the estimated effects of number of infant deaths per 100,000 live births compared to a negligible investment scenario is beyond 100,000 in two of the states, suggesting these estimates are indeed unstable. Thus, we find the second explanation the most likely. In any case, both the quality and core models suggest limited effect of PRONAF investment as the majority of Brazils 27 states are unaffected.

Also the effect of total PRONAF investment on natural vegetation cover in two biomes (the Amazon and Cerrado) changes from not significant in the core model to significant in the quality model. Because the overall (grand) effect of investment is significant, the interpretation of these biome effects are that they are not significantly different to the overall effect of investment. The magnitude and direction of effect of investment in the Amazon and Cerrado is almost identical between the core and quality models, however, which does suggest a certain level of reliability in these effects. The reductions in sample size for the quality model is limited (33% reduction in the Amazon and 2% reduction in the Cerrado). We, thus find it more likely that excluding the more unreliable municipality data (caused by for instance larger areas of natural vegetation not recorded due to cloud cover) made it easier for the model to pick up on these significant effects.

The most noticeable differences between the quality control and core models are found in the Zero Hunger and Bolsa Familia models on child malnutrition in the poorer sectors of society (SIAB data). Whereas core models suggest investment is driving a significant non-beneficial increase in child malnutrition across Brazil, the quality models shows no significant effects. In addition, the direction of effect changes and the investment parameter estimates suggest an average reduction in child malnutrition, though we note the 95% confidence intervals include zero. Given this inconsistency we interpret the core results more cautiously.

Spatial autocorrelation. We test for spatial autocorrelation by running two-sided Moran’s I tests on all core model residuals as well as model residuals from the covariate balancing stage (CBGPS). However, because only the parametric CBGPS models offer model residuals (Fong et al., 2017) we create our own propensity score models, i.e. linear regressions where investment is the function of predictor variables, and look for signs of spatial autocorrelation in those model residuals.

Two distinct spatial neighbourhood matrices are used to accommodate differences in spatial trends. First, a neighbourhood matrix based on touching municipality borders is calculated, thus reflecting similarities in values caused for instance by regional municipality collaborations (structural factors). Secondly, a pure distance measure is created to capture possible physical factors, with neighbourhoods defined as the inverse distance between each municipality centre, though capped at 0.75 of the max given the extreme sizes of some Brazilian municipalities. Presence of significant spatial-autocorrelation is considered when Morans I values are far from 0 and corresponding p-values are below 0.05. Morans I values nearer +1 indicated presence of clustering while values nearer -1 indicate dispersion (Griffith, 2009).

We find no presence of spatial autocorrelation in neither the propensity score models built nor in the subsequent weighted outcome models. Of the 24 propensity score models only one had significant Morans I values when based on a municipality border neighbourhood matrix, and one when a distance based matrix was used. The corresponding Morans I values were, however, very close to 0 (-0.018 and -0.008, respectively) and thus in effect show no signs of spatial autocorrelation. Likewise, five and seven outcome model residuals had significant Morans I values, based on a border and distance matrix respectively, but again Morans I values were close to 0 (range 0.007 to 0.029). Based on this, we conclude that our observations are independent from each other in both models that deal with the non-random treatment allocation process and in subsequent estimation of impact of investment on our outcomes of interest. It is also a strong indicator of no presence of (spatially determined) unmeasured confounders.

Endogeneity. Third, we look for presence of endogeneity between model error terms and investment variables. Though a Hausman test is commonly used to test for endogeneity, Guo and Fraser (2015) note that to implement the Hausman test the source of endogeneity, i.e. the omitted variable that causes the correlation between the error term and the endogenous explanatory variable, needs to be known, yet in observational studies it often is not. In addition, finding appropriate instrumental variables needed for the Hausman test is often difficult. This is the case for our models. In the absence of the Hausman test we rather assess whether the error term (model residuals) and investment variable are correlated running a series of non-parametric Spearmans' rho correlation tests.

The correlation coefficients (Spearmans rho) between model residuals and the model investment variable are very low for all 24 core models and range from -0.133 to 0.065. Thus, we conclude there is no evidence of endogeneity between our investment variables and model error term. This result is also a further suggestion that there is unlikely unmeasured confounders which influence our main treatment variables and outcomes.

7.2. Supplementary Tables and Graphs

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	
$\log_{10}(Kcal^{pc})$	$\log_{10}(ZH^{pc})$* State $\log_{10}(BF^{pc})$* State $\log_{10}(PRONAF^{pc})$* State	✓	✓	✓		B		✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,940
$\log_{10}(Protein^{pc})$	$\log_{10}(ZH^{pc})$* State $\log_{10}(BF^{pc})$* State $\log_{10}(PRONAF^{pc})$* State	✓	✓	✓			B	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,940
$\log_{10}(Poverty^{Census})$	$\log_{10}(ZH^{pc})$* State + $\log_{10}(ZH^{pc})$^2 $\log_{10}(BF^{pc})$* State $\log_{10}(PRONAF^{pc})$* State	✓	✓	✓		✓		B				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,976
$\log_{10}(Poverty^{SIAB})$	$\log_{10}(ZH^{pc})$ $\log_{10}(BF^{pc})$* State $\log_{10}(PRONAF^{pc})$* State	✓	✓	✓		✓		B				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		3,808
Child malnutrition^{SIAB}	$\log_{10}(ZH^{pc})$ $\log_{10}(BF^{pc})$* State $\log_{10}(PRONAF^{pc})$	✓	✓	✓		✓		✓		B		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		3,851
Infant mortality^{Census}	$\log_{10}(ZH^{pc})$ $\log_{10}(BF^{pc})$ $\log_{10}(PRONAF^{pc})$	✓	✓	✓		✓		✓	B			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,976
Infant mortality^{SIAB}	$\log_{10}(ZH^{pc})$ $\log_{10}(BF^{pc})$ $\log_{10}(PRONAF^{pc})$	✓	✓	✓		✓		✓	B			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		4,331
$\log_{10}(Natural\ vegetation^{km2})$	$\log_{10}(ZH^{pc})$* Biome^{6cat} + $\log_{10}(ZH^{pc})$^2 $\log_{10}(BF^{pc})$* Biome^{6cat} $\log_{10}(PRONAF^{pc})$* Biome^{6cat} + $\log_{10}(ZH^{pc})$^2	✓	✓		✓			✓			B	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	4,924

Pc = per capita. B = baseline conditions of the outcome variable. N = model sample size. Outcome years correspond to 2010 for 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 Zero Hunger, Bolsa Familia 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. Zero Hunger investment that is not captured in the sub-programme (included in the Bolsa Familia and PRONAF models only), 2. State, 3. Biome^{13cat}, 4. Biome^{6cat}, 5. Kcal^{pc}, 6. Protein^{pc}, 7. 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 and 22. Protected area^{km2}. The same ticks/Bs indicates predictor variables used to create the CBGPS weights also included in each model, i.e. when we model Treatment (Y) as the function of predictor variables. Some models include an interaction term between treatment and state or biome (indicated by *), and a quadratic term (^2). 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. 13. Pasture area, and 14. Small-scale farm area is for 2006 (the only available year with data). 7. baseline 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 Poverty^{SIAB} (which corresponds to year 2004) because the geographical coverage of MPI^{Census} better matches the coverage of these outcome variables, i.e. the whole municipality as opposed to only the poorer regions as covered by Poverty^{SIAB}. 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	157,902	442,278
		Baseline	84,420	240,796
Protein (gram pc/day)	Grams of protein produced per capita per day in 2013 and 2004	Endpoint	1,975	5,665
		Baseline	1,410	3,916
Poverty[Census]	Multidimensional poverty index for the entire population in 2010 and 2000	Endpoint	0.058	0.031
		Baseline	0.116	0.06
Poverty[SIAB]	Multidimensional poverty index in the poorer sectors of society in 2013 and 2004	Endpoint	0.059	0.039
		Baseline	0.07	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	253	290
		Baseline	665	458
Infant mortality[Census]	Number of infant (<1 year) deaths per 100,000 live births for the entire population in 2010 and 2000	Endpoint	1,958	717
		Baseline	3,393	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	2,255	11,072
		Baseline	2,547	2,589
Natural vegetation cover (km^2)	Total area (km^2) under natural vegetation in 2013 and 2004	Endpoint	1,078	5,331
		Baseline	1,103	5,402
Treatment variables:				
ZH (R$/pc)	Total per capita Zero Hunger investment in Brazilian Reals, i.e. sum of per capita Bolsa Familia, PRONAF, PAA and PNAE for 2000-2010; and 2004-2013	Total	2,550; 3,829	2,704; 3,948
BF (R$/pc)	Total Bolsa Familia investment per capita for 2004-2010; and 2004-2013	Total	692; 1,216	398; 696
PRONAF (R$/pc)	Total PRONAF investment per capita for 2000-2010; and 2004-2013	Total	1,716; 2,439	2,796; 4,118
Confounding variables:				
Poverty[Census]	Multidimensional poverty index for the entire population in 2000	Baseline	0.116	0.06
GDP[Public Service] (R$/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
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)	Municipality area for 2000; and 2004; and municipality area without cloud cover in 2004 and 2013	Baseline	1,630; 1,619; 1,573	5,939; 5,902; 5,712
Protected area (km^2)	Total area under strict-, sustainable use- and indig. 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 corresponding 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 model sample (n = 4,976) and the largest 2004-2013 sample (n = 4,940). When only one confounding variable value is recorded largest sample in which the variable features is used.

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

	Zero Hunger				Bolsa Familia				PRONAF			
Outcomes	Coef±S.E.	P	Int.	R^2	Coef±S.E.	P	Int.	R^2	Coef±S.E.	P	Int.	R^2
$Kcal^{pc}$	0.01±0.02	0.81	S	0.94	0.01±0.02	0.75	S	0.93	0.01±0.01	0.21	S	0.94
$Protein^{pc}$	0.08±0.02	<0.0001	S	0.96	0.09±0.02	<0.0001	S	0.95	0.04±0.01	<0.001	S	0.96
$Poverty^{Census}$	-0.02±0.01	0.01	S	0.75	0.03±0.01	0.003	S	0.75	-0.02±0.01	<0.0001	S	0.75
$Poverty^{Census}$ (quadratic)	-0.01±0.002	0.01			0.01±0.01	0.01						
$Poverty^{SIAB}$	0.02±0.01	0.19		0.6	0.07±0.01	<0.0001		0.62	-0.01±0.02	0.49		0.6
$ChildMaln.^{SIAB}$	-0.06±0.04	0.15		n.a.	-0.07±0.06	0.24		n.a.	0.01±0.03	0.67		n.a.
$InfantMort.^{Census}$	0.01±0.23	0.97		0.14	0.04±0.27	0.89		0.13	-0.01±0.17	0.95		0.15
$InfantMort.^{SIAB}$	0.06±0.05	0.23		n.a.	0.27±0.07	<0.0001		n.a.	-0.16±0.15	0.27	S	n.a.
$NaturalVeg.^{km2}$	-0.04±0.01	<0.001	B	0.99	-0.003±0.002	0.06		0.99	-0.04±0.01	0.002	B	0.99
$NaturalVeg.^{km2}$ (quadratic)	-0.004±0.001	0.001							-0.004±0.001	0.001		

Outcomes are daily per capita (pc) kilocalorie and protein production, 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 and in the poorer sectors (Census and SIAB), and area of natural vegetation. Model coefficients are reported ± one standard error. S and B indicate models that include significant interactions between investment in Zero Hunger programmes or sub-programmes and state or biome (natural vegetation models). 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, 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} using 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.

Table S4. 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	Kcal USDA	**Kcal used**	Protein FBA/USP	Protein USDA	**Protein used**
(a)							
Sugarcane		-	3,750	**3,750**	-	0	**0**
Soyabeans		3,630	4,460	**4,045**	405	360	**382.5**
Maize		-	3,650	**3,650**	-	90	**90**
Rice		3,400	3,650	**3,525**	78.1	70	**74**
Cassava		1,330	1,600	**1,465**	13	10	**11.5**
Milk		650	600	**625**	29.7	30	**29.8**
(b)							
	Kg meat/ animal						
Cattle	134.5[1]	1,388	2,340	**1,864**	200.7	190	**195.4**
Buffalo	218.5[2]	-	1,090	**1,090**	-	210	**210**
Chicken	1.7[3]	2,090	-	**2,090**	171	-	**171**
Sheep	6.5[4]	1,090	-	**1,090**	207.4	-	**207.4**
Goat	5.8[5]	-	1,090	**1,090**	-	210	**210**
Pig	45.4[6]	1,720	1,850	**1,788**	198.7	195	**196.8**

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 [1]Nunes et al., 2015, [2]Peixoto et al., 2012, [3]Faria et al., 2010, [4]Cardoso et al., 2013, [5]Maria et al., 2015 and [6]Bertol et al., 2013. Nutrient values are taken from the Brasilfoods (FBA/USP, 2008) and USDA database (USDA, 2008), the average of the two used when possible, expressed here as kilocalories and grams of protein per kg

Table S5. Data included to create the multi-dimensional poverty indices Poverty-Census and Poverty-SIAB.

<table>
<tr><th></th><th colspan="2">Poverty-Census</th><th colspan="2">Poverty-SIAB</th></tr>
<tr><td rowspan="3">Health</td><td colspan="2">Infant mortality
(infant deaths per 1,000 births)</td><td colspan="2">Infant mortality
(infant deaths per 1,000 births)</td></tr>
<tr><td colspan="2" rowspan="2">Life expectancy deprivation
(deviation from expected living age w/global min and max years): 1-((LifeExpectancy-20)/(85-20))</td><td rowspan="2">Child malnutrition
(underweight per 100 weighted)</td><td>Underweight at birth
(per 100 weighed)</td></tr>
<tr><td>Underweight age 1-2
(per 100 weighed)</td></tr>
<tr><td>Education</td><td colspan="2">No school attendance
(% 7-14 year olds that do not attend primary school)</td><td colspan="2">No school attendance
(% 7-14 year olds that do not attend primary school)</td></tr>
<tr><td rowspan="9">Living standard</td><td colspan="2">No electricity
(% people without access to electricity)</td><td colspan="2">No electricity
(% people* without access to electricity)</td></tr>
<tr><td colspan="2">Unsafe water
(% people without piped water)</td><td colspan="2">Unsafe water
(% people* without piped water)</td></tr>
<tr><td colspan="2">Inadequate sanitation
(% people* without public system or septic tank)</td><td colspan="2">Inadequate sanitation
(% people* without public system or tank)</td></tr>
<tr><td rowspan="6">No assets
(% people without access to:)</td><td>TV</td><td colspan="2" rowspan="6">Inadequate walls
(% people*living in houses with inadequate walls such as cardboard, plastic and straw)</td></tr>
<tr><td>Radio</td></tr>
<tr><td>Telephone</td></tr>
<tr><td>Car</td></tr>
<tr><td>Fridge/freezer</td></tr>
<tr><td>Washing machine</td></tr>
</table>

Data included to create Poverty-Census is based on the Brazilian demographic sensus (IBGE, 2010) while Poverty-SIAB on the national primary information system (SIAB) (Ministerio da Saude, 2015). 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 MPIs ranging 0-1 where 1 equals complete poverty

Table S6. 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 (2017), 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 S7. Robustness check validating the accuracy of MapBiomas (MB), comparing its extent of natural vegetation to alternative vegetation maps

Biome	**Alternative land use**	**Resolution**	**Year**	**% cover MB**	**% cover Alternative**	**Spearman's rho correlation municipal km^2**	**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 (2017) 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). Alternative maps (besides for the Amazon) were available in vector form at scale 1:250,000. TerraClass has as minimum detected area of approximately 6.25 ha (i.e. 250 m) (MMA et al., 2015). First, natural vegetation is considered as proportion of total biome area (% cover). Then, Spearmans rho correlations are based on the km2 natural vegetation value per municipality, here including only municipalities with <1% difference in municipality size between maps (<5% difference in the Amazon given a consistent 4% divergence in size caused by the different processing of the MB and TerraClass map). N refers to the number of municipalities included for the correlation analysis. The % cover analysis is based on all municipalities within each biome. The slight 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

Table S8. 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	Inconsistent municipality borders	Multiple to single municipality (Year 1 – Year 2)	Spatial inconsistency	All	4 – 45
	1.1	Inconsistent municipality borders	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	> 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} , 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	> 5%	Spatial inconsistency	Natural vegetation	323

Criteria seven is based on formal suggestions for SIAB data (Ministerio da Saude, 2003). The final column reports the number of municipalities excluded based on a sequential exclusion

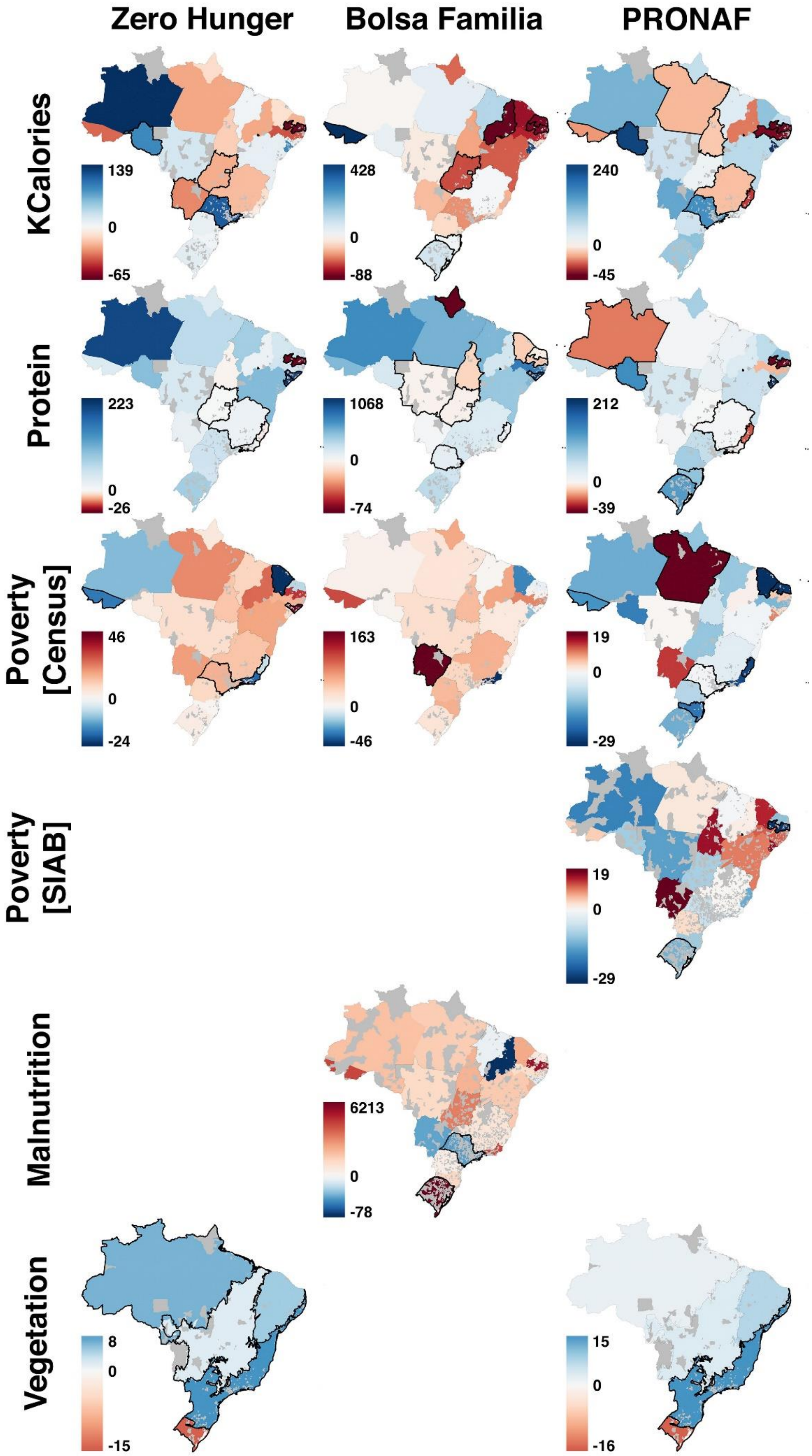

Zero Hunger
Bolsa Familia
PRONAF
KCalories
139
0
-65
428
0
-88
240
0
-45
Protein
223
0
-26
1068
0
-74
212
0
-39
Poverty [Census]
46
0
-24
163
0
-46
19
0
-29
Poverty [SIAB]
19
0
-29
Malnutrition
6213
0
-78
Vegetation
8
0
-15
15
0
-16

Fig. S1. Quality sample robustness check of relative impact of Zero Hunger, Bolsa Familia and PRONAF investment given a spatially uniform (median) investment level (column 1-3) on daily per capita kilocalorie production, daily per capita protein production, poverty in the entire population (Census), 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 (1^{st} percentile value) programme investment level and a spatially uniform median programme investment level investment level. Relative impact calculations are based on robust multivariable regression models of a covariate-balanced sample restricting the analysis to the highest quality data (Table S3). 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

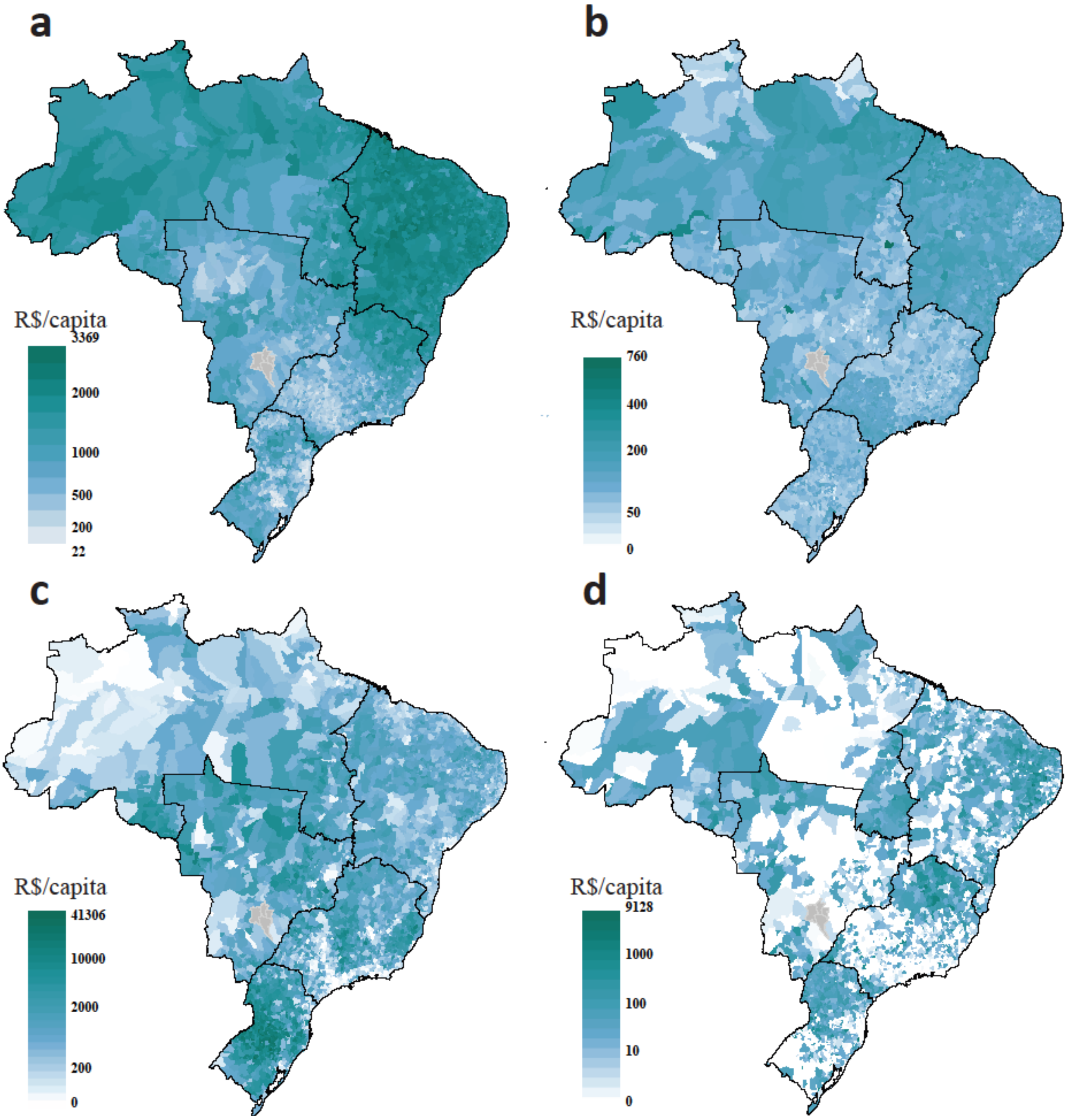
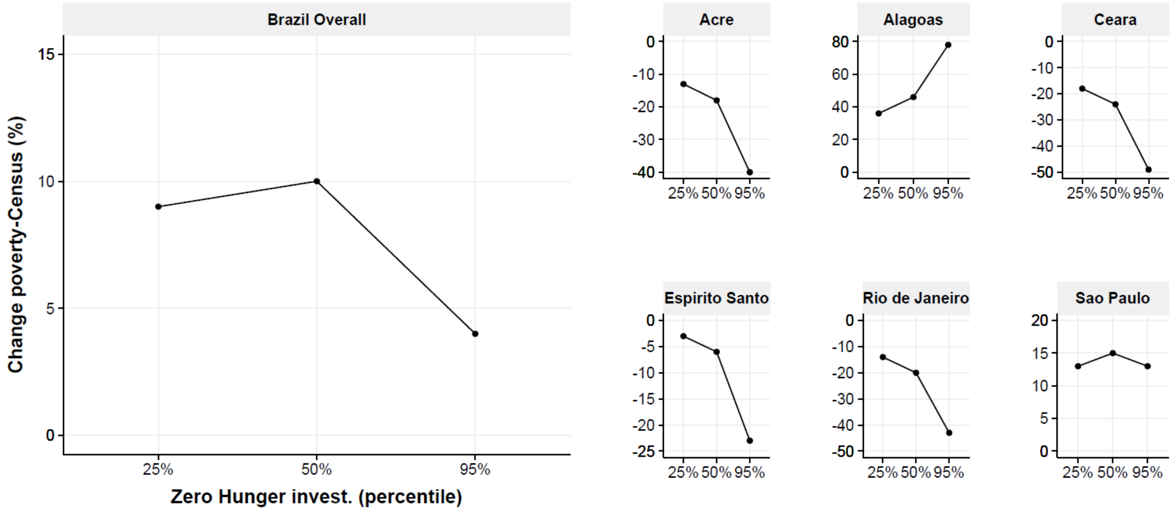


Fig. S2. Total investment per capita in Brazilian reals (R$) from 2004-2013 for the main Zero Hunger sub-programmes **a** Bolsa Familia, **b** PNAE, **c** PRONAF and **d** PAA, available at www.dados.gov.br/www.mds.gov.br, showing great spatial variation in investment within and across programmes. Grey areas indicate municipalities not included. Dark borders show administrative region borders

a)



b)

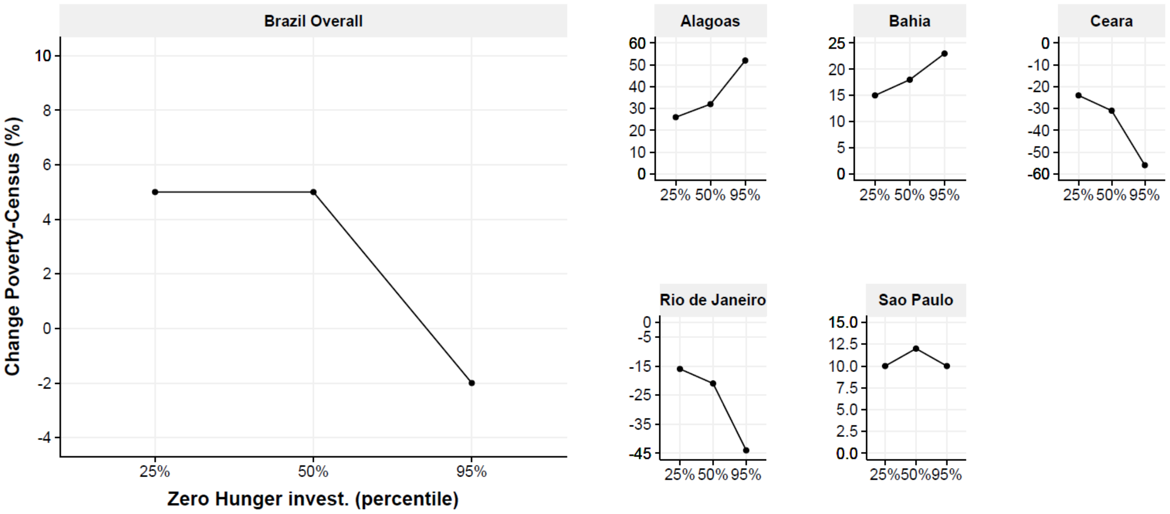


Fig. S3. Non-linear effects from a) Zero Hunger investment on Poverty-Census based on core model results and b) Zero Hunger investment on Poverty-Census based on quality robust model results. It shows change in outcome from three investment levels: the 25th, 50th and 95th percentile investment level, relative to negligible investment. Each panel shows the overall effect of investment for Brazil, and the effects for states which have a significantly different effect to Brazil overall, based on robust regression models with a significant state-investment term and a significant quadratic investment term

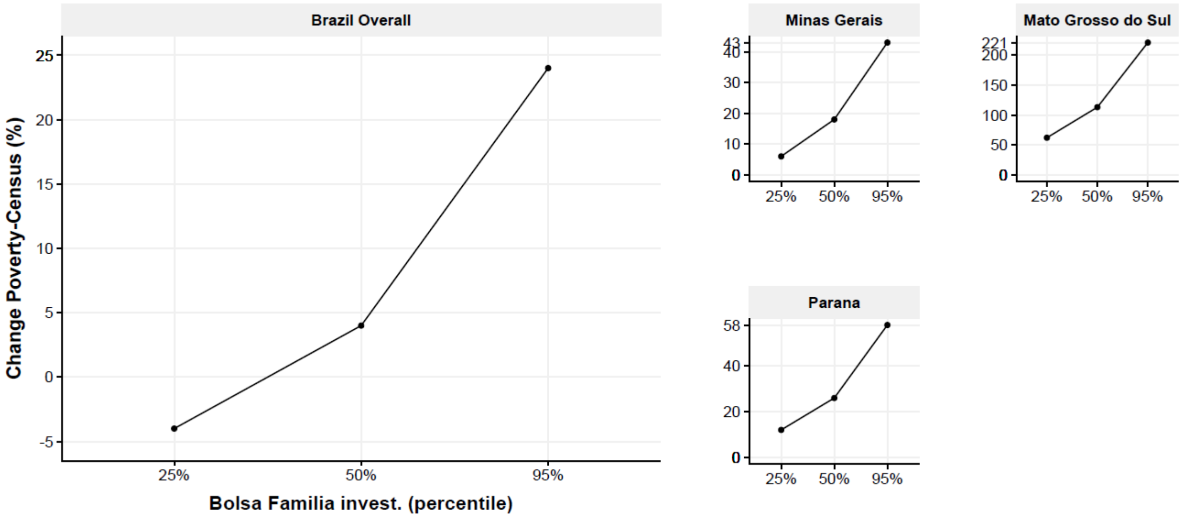
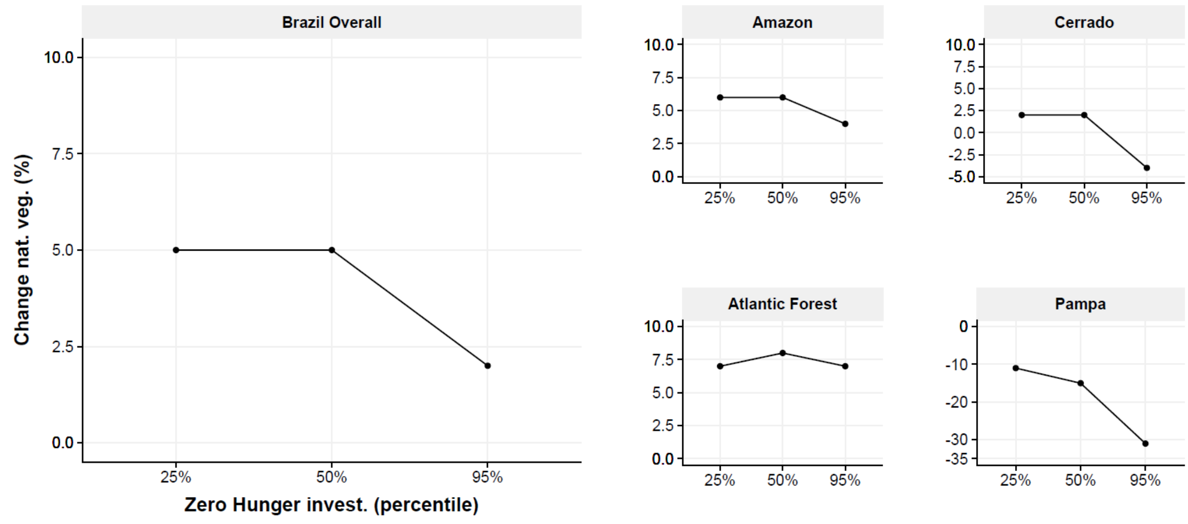


Fig. S4. Non-linear effect from Bolsa Familia investment on Poverty-Census based on quality robust model results. It shows change in outcome from three investment levels: the 25th, 50th and 95th percentile investment level, relative to negligible investment. Each panel shows the overall effect of investment for Brazil, and the effects for states which have a significantly different effect to Brazil overall, based on robust regression models with a significant state-investment term and a significant quadratic investment term

a)



b)

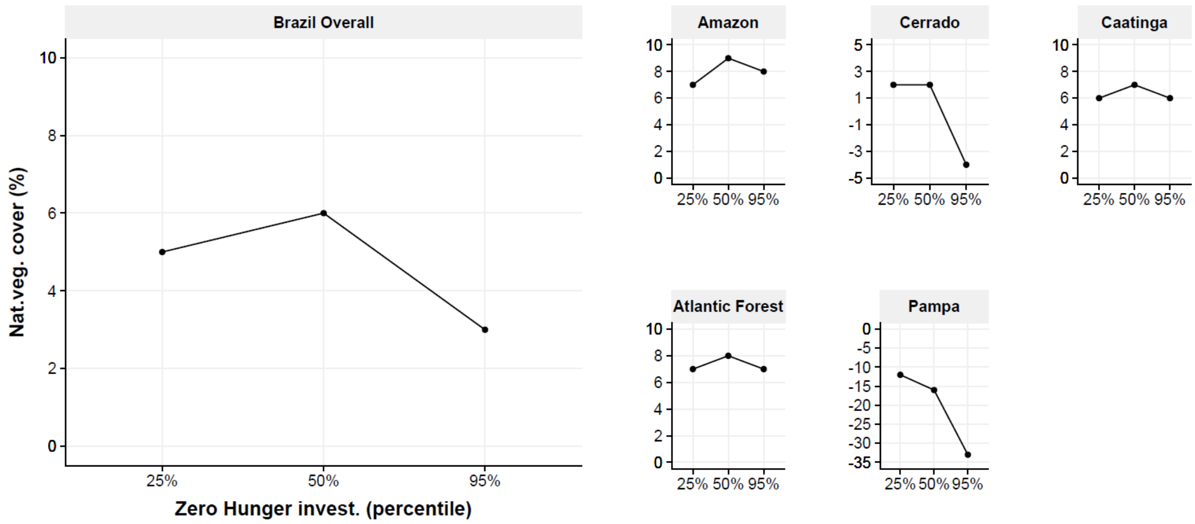
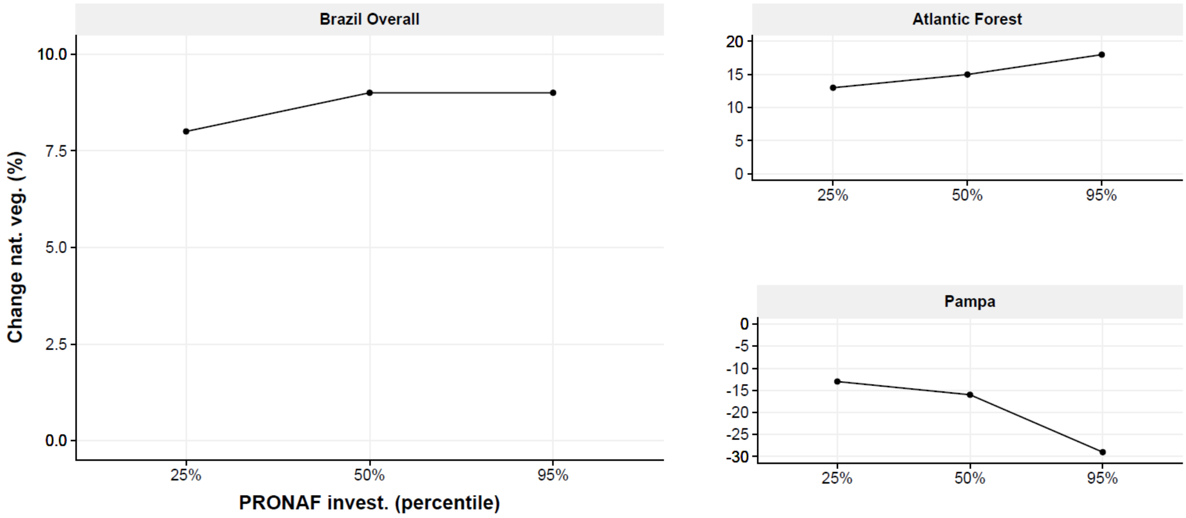


Fig. S5. Non-linear effect from a) Zero Hunger investment on natural vegetation cover based on core model results and b) Zero Hunger investment on natural vegetation cover based on quality robust model results. It shows change in outcome from three investment levels: the 25th, 50th and 95th percentile investment level, relative to negligible investment. Each panel shows the overall effect of investment for Brazil, and the effects for biomes which have a significantly different effect to Brazil overall, based on robust regression models with a significant biome-investment term and a significant quadratic investment term

a)



b)

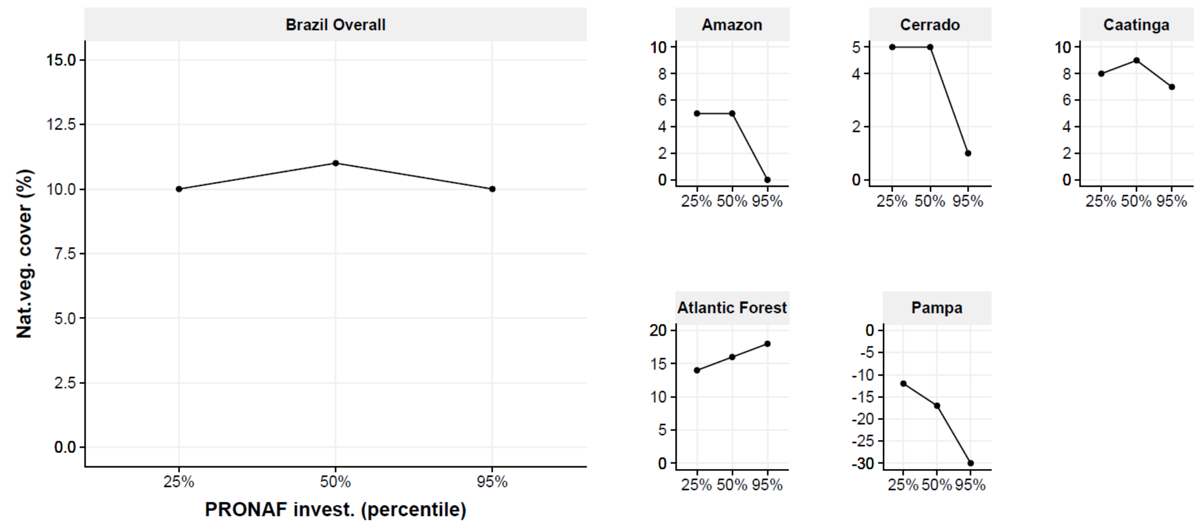


Fig. S6. Non-linear effect from a) PRONAF investment on natural vegetation cover based on core model results and b) PRONAF investment on natural vegetation cover based on quality robust model results. It shows change in outcome from three investment levels: the 25^{th}, 50^{th} and 95^{th} percentile investment level, relative to negligible investment. Each panel shows the overall effect of investment for Brazil, and the effects for biomes which have a significantly different effect to Brazil overall, based on robust regression models with a significant biome-investment term and a significant quadratic investment term

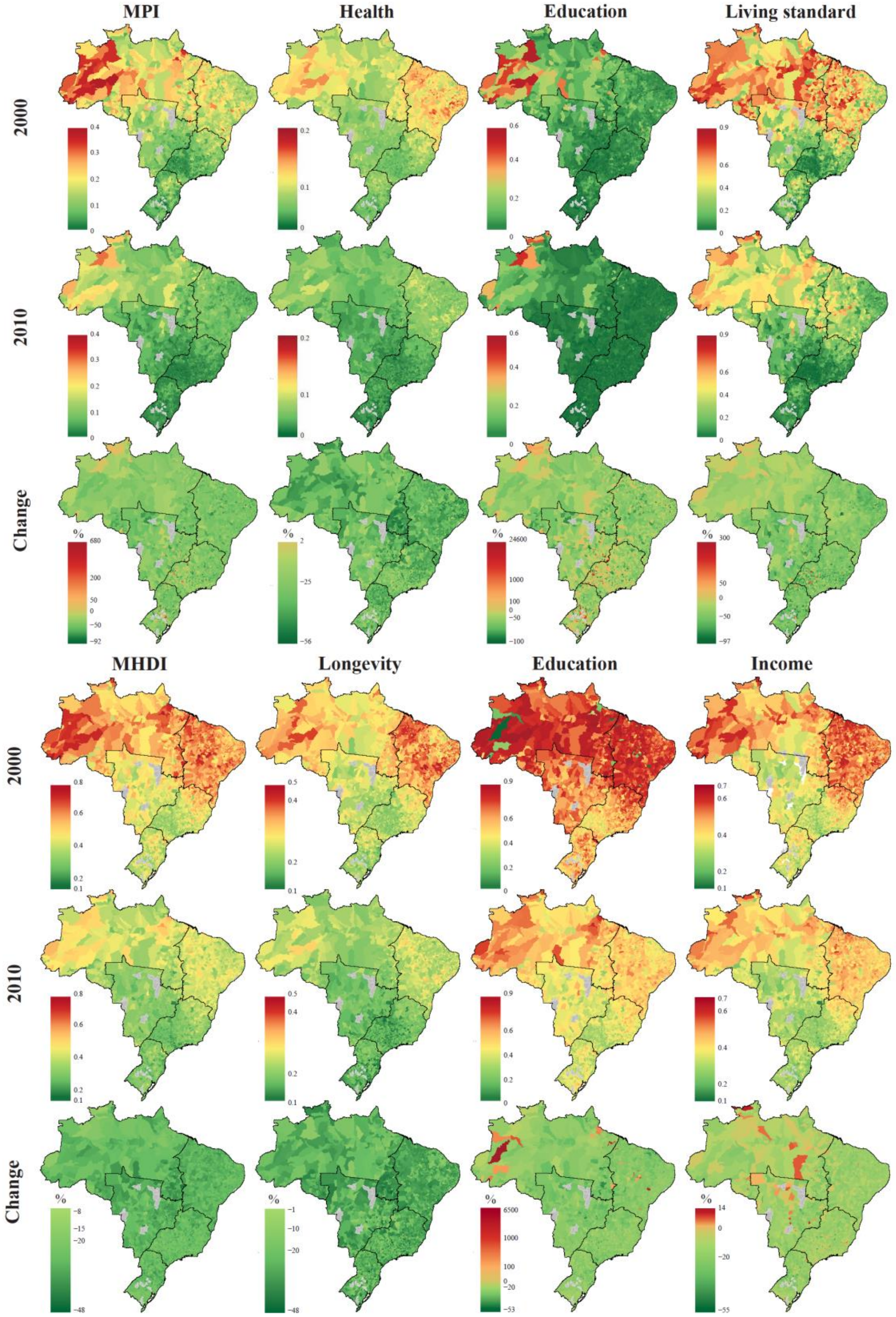


Fig. S7. High consistency between Poverty-Census (MPI) overall and its three dimensions Health, Education and Living Standard for 2000 and 2010 (top 3 rows), and the Brazilian Municipal Human Development Index (MHDI) (when negatively loaded) and its three dimensions Longevity, Education and Income (bottom 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

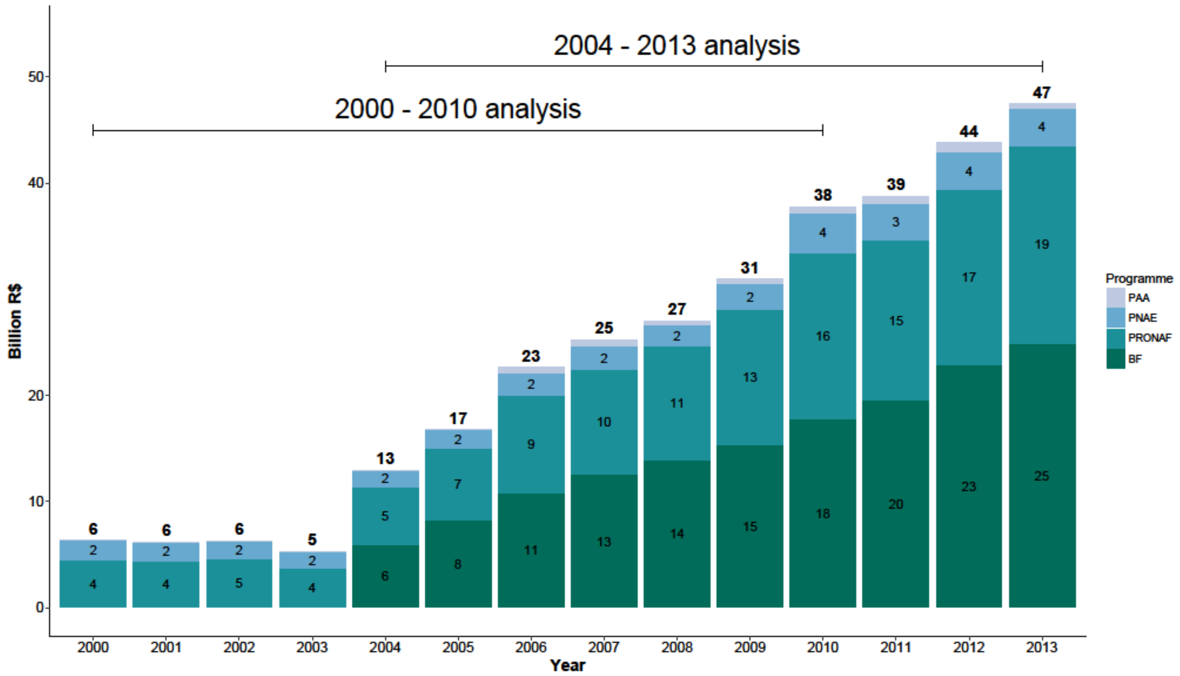


Fig. S8. Annual investments in the four main Zero Hunger sub-programmes Bolsa Familia (BF), PRONAF, PNAE and PAA available at www.dados.gov.br/www.mds.gov.br, showing a gradual increase in annual investments and predominance of BF and PRONAF to total Zero Hunger. Horizontal lines indicate investment values included in the respective Zero Hunger and food security 2000-2010 and 2004-2013 analyses. All values are expressed in billion Reals (R$) and adjusted for inflation with base year 2013

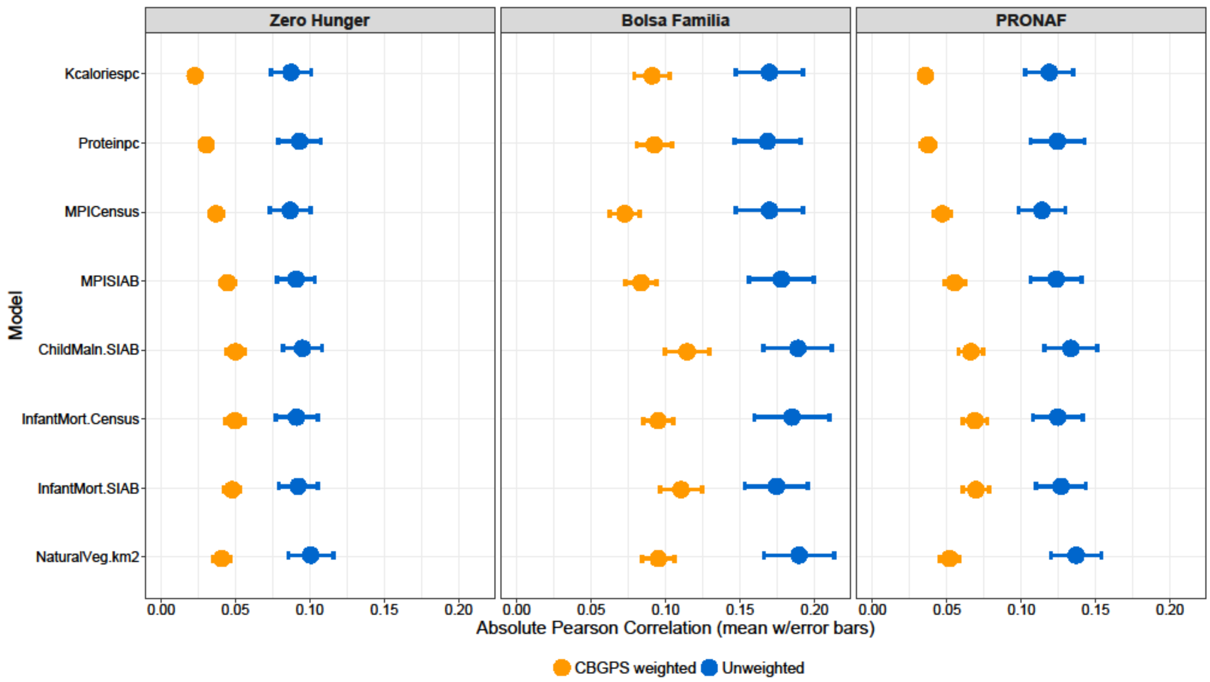


Fig. S9. Great covariate balance achieved following the Covariate balancing generalized propensity score (CBGPS) method from Fong et al. (2017). Orange circles shows average absolute Pearson correlation between the Zero Hunger, Bolsa Familia and PRONAF investment variable and model covariates (predictor variables) for all models when CBGPS weights are included in the model. Blue circles are the unweighted average correlations. Lines represent error bars.

7.3. References.

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, *95*(7–8), 476–487. http://doi.org/10.1016/j.jpubeco.2010.11.006

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences*, *105*(42), 16089–16094. http://doi.org/10.1073/pnas.0800437105

Assunção, J., Gandour, C., Rocha, R., & Rocha, R. (2013). *Does Credit Affect Deforestation? Evidence from a Rural Credit Policy in the Brazilian Amazon*. Retrieved from http://climatepolicyinitiative.org/wp-content/uploads/2013/01/Does-Credit-Affect-Deforestation-Evidence-from-a-Rural-Credit-Policy-in-the-Brazilian-Amazon-Technical-Paper-English.pdf

Aster GDEM. (2011). ASTER GDEM. Retrieved October 9, 2015, from http://gdem.ersdac.jspacesystems.or.jp/

Atlas Brazil. (2013). The MHDI: Atlas of Human Development in Brazil. Retrieved November 3, 2015, from http://www.atlasbrasil.org.br/2013/en/o_atlas/idhm/

Banco Central do Brasil. (2017). Crèdito Rural. Retrieved August 31, 2017, from http://www.bcb.gov.br/pt-br/#!/n/credrural

Banks-Leite, C., & Ewers, R. M. (2009). Ecosystem Boundaries. *Encyclopedia of Life Sciences*, 1–8. http://doi.org/10.1002/9780470015902.a0021232

Beguería, S., & Vicente Serrano, S. M. (2014, November 11). SPEIbase v.2.3. Retrieved from http://digital.csic.es/handle/10261/104742

Belsley, D. A., Kuh, E., & Welsch, R. E. (2005). *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. John Wiley & Sons.

Berdegué, J. a, & Fuentealba, R. (2011). Latin America: The state of smallholders in agriculture. *Paper Presented at the IFAD Conference on New Directions for Smallholder Agriculture, Session 3*. Retrieved from http://193.194.138.127/events/agriculture/doc/papers/berdegue.pdf

Burgess, R., & Pande, R. (2005). Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review*, *95*(3), 780–795. http://doi.org/10.1257/0002828054201242

Coxe, S., West, S. G., & Aiken, L. S. (2009). The Analysis of Count Data : A Gentle Introduction to Poisson Regression and Its Alternatives. *Journal of Personality Assessment*, *91*(2), 121–136. http://doi.org/10.1080/00223890802634175

Croux, C., Dhaene, G., & Hoorelbeke, D. (2003). *Robust standard errors for robust regression estimators* (03.16 No. Discussion Paper Series (DPS)). Leuven.

Digital.csic. (2014). Global SPEI database. Retrieved August 31, 2015, from http://sac.csic.es/spei/database.html

European Space Agency. (2014). ESA CCI Land cover. Retrieved October 9, 2015, from http://www.esa-landcover-cci.org/

FBA/USP. (2008). Tabela Brasileira de Composição de Alimentos: Brasilfoods. Retrieved April 1, 2016, from http://www.intranet.fcf.usp.br/tabela/index.asp

FGM. (2013). IBGE: versão atualizada da Base Cartográfica Contínua do Brasil está disponível. Retrieved May 1, 2016, from http://fgm-go.org.br/noticias/ibge-versao-atualizada-da-base-cartografica-continua-do-brasil-esta-disponivel/

Fischer, G., Velthuizen, H. Van, Shah, M., & Nachtergaele, F. (2002). *Global Agro-ecological Assessment for Agriculture in the 21st Century : Methodology and Results*. *Analysis* (Vol. RR-02-02). http://doi.org/http://www.iiasa.ac.at/Admin/PUB/Documents/RR-02-002.pdf

Fong, C., Hazlett, C., & Imai, K. (2017). Covariate Balancing Propensity Score for a Continuous Treatment : Application to the Efficacy of Political. *Forthcoming in Annals of Applied Statistics*.

Glickhouse, R. (2015). Brazil Update: Historic Drought Takes Toll on Agriculture. Retrieved August 25, 2015, from http://www.as-coa.org/articles/brazil-update-historic-drought-takes-toll-agriculture

Griffith, D. A. (2009). Methods: spatial autocorrelation. In R. Kitchin & N. Thrift (Eds.), *International Encyclopedia of Human Geography* (pp. 396–402). NY: Elsevier.

Guedes, G., Costa, S., & Brondizio, E. (2012). Revisiting the hierarchy of urban areas in the Brazilian Amazon: a multilevel approach. *Changes*, *29*(6), 997–1003. http://doi.org/10.1016/j.biotechadv.2011.08.021.Secreted

Guo, S., & Fraser, M. W. (2015). Counterfactual Framework and Assumptions. In *Propensity Score Analysis: statistical methods and applications* (p. 448). SAGE Publications Ltd.

Hoef, J. M. Ver, & Boveng, P. L. (2007). Quasi-Poisson vs . Negative Binomial Regression : How Should We Model Overdispersed Count Data: *Ecology*, *88*(11), 2766–2772.

IBGE. (2006). Censo Agropecuário (Agricultural census). Retrieved November 25, 2014, from http://www.ibge.gov.br/english/estatistica/economia/agropecuaria/censoagro/2006_segunda_apuracao/default_tab_pdf.shtm

IBGE. (2010). Censo Demografico. Retrieved March 27, 2018, from https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2010/inicial

IBGE. (2016). Produção Agrícola Municipal. Retrieved May 1, 2016, from http://www.sidra.ibge.gov.br/bda/pesquisas/pam/

IBGE, & MMA. (2004). Mapa de Biomas e de Vegetação. Retrieved May 1, 2016, from http://www.ibge.gov.br/home/presidencia/noticias/21052004biomashtml.shtm

JRC Science Hub. (2014). Global Environmental Monitoring - Map showing the travel time to major cities - JRC Science Hub - European Commission. Retrieved October 9, 2015, from https://ec.europa.eu/jrc/en/scientific-tool/global-environmental-monitoring-map-showing-travel-time-major-cities

Junior, M. (2009). Governo gastou R$ 62 bilhões com Fome Zero desde 2003. *Contas Abertas*.

MapBiomas. (2017). Coleções MAPBIOMAS. Retrieved August 20, 2017, from http://mapbiomas.org/pages/database/mapbiomas_collection

Ministerio da Saude. (2003). *Sistema de Informação da Atenção Básica SIAB Indicadores 2002*.

Ministerio da Saude. (2015). SIAB: Sistema de Informação de Atenção Básica. Retrieved March 18, 2015, from http://www2.datasus.gov.br/DATASUS/index.php?area=0205

MMA. (2007). *Priority Areas for the Conservation , Sustainable Use and Benefit Sharing of Brazilian Biological Diversity*. Brasilia: Ministry of the Environment.

Moreira, M. R., & Escorel, S. (2009). Municipal Health Councils of Brazil: a debate on the democratization of health in the twenty years of the UHS. *Ciencia & Saude Coletiva*, *14*(3), 795–806.

Mourao, L., Ferreira, M. C., & Jesus, A. M. de. (2009). Evaluation of the Brazilian Family Grant Program : A Quasi-Experimental Study in the State of Rio de Janeiro. *Psicologia: Reflexao e Critica*, 719–729.

Oldekop, J. A., Sims, K. R. E., Whittingham, M. J., & Agrawal, A. (2018). An upside to globalization : International outmigration drives reforestation in Nepal. *Global Environmental Change*, *52*(February 2017), 66–74. http://doi.org/10.1016/j.gloenvcha.2018.06.004

Rasella, D., Aquino, R., & Barreto, M. L. (2010). 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. http://doi.org/10.1186/1471-2458-10-380

Remans, R., Wood, S. a., Saha, N., Anderman, T. L., & DeFries, R. S. (2014). Measuring nutritional diversity of national food supplies. *Global Food Security*, 1–9. http://doi.org/10.1016/j.gfs.2014.07.001

Rosenzweig, M. R., & Wolpin, K. I. (1993). 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. *Journal of Political Economy*, *101*(2), 223–244. http://doi.org/10.1086/261874

Rousseeuw, P., Croux, C., Todorov, V., Ruckstuhl, A., Salibian-barrera, M., Verbeke, T., … Maechler, M. M. (2015). Package 'robustbase.' *R Topics*.

Sietz, D., Untied, B., Walkenhorst, O., Lüdeke, M. K. B., Mertins, G., Petschel-Held, G., & Schellnhuber, H. J. (2006). Smallholder agriculture in Northeast Brazil: Assessing heterogeneous human-environmental dynamics. *Regional Environmental Change*, *6*(3), 132–146. http://doi.org/10.1007/s10113-005-0010-9

Silva, J. G. da, Grossi, M. E. Del, & França, C. G. de. (2011). *The Fome Zero (Zero Hunger) Program: The brazilian experience*. (J. G. da Silva, M. E. Del Grossi, & C. G. de França, Eds.). Brasilia.

Soares-Filho, B., Moutinho, P., Nepstad, D., Anderson, A., Rodrigues, H., Garcia, R., … Maretti, C.

(2010). Role of Brazilian Amazon protected areas in climate change mitigation. *Proceedings of the National Academy of Sciences*, *107*(24), 10821–10826. http://doi.org/10.1073/pnas.0913048107

Stauffer, C. (2013). Worst drought in decades hits Brazil’s Northeast. Retrieved August 25, 2015, from http://uk.reuters.com/article/2013/01/04/us-brazil-drought-idUSBRE9030HM20130104

UNDP-IPC. (2013). *Structured Demand and Smallholder Farmers in Brazil : the Case of PAA and PNAE*. Brasilia.

USDA. (2008). USDA National Nutrient Database for Standard Reference, Release 21. Retrieved April 1, 2016, from http://nutritiondata.self.com/facts/lamb-veal-and-game-products/4738/2

World Bank. (2008). *World Development Report 2008: Agriculture for Development*. Washington DC, USA.

Xavier, A. C., King, C. W., & Scanlon, B. R. (2015). Daily gridded meteorological variables in Brazil (1980-2013). *International Journal of Climatology*. http://doi.org/10.1002/joc.4518

Young, H., & Jaspars, S. (2009). *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*.

Chapter 3

Mechanisms driving impact of the Zero Hunger programme on food security and environmental sustainability amongst small-scale farmers

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Abstract

Social protection programmes are common strategies to deliver improvements in social conditions. Brazil's flagship Zero Hunger programme has been hailed as a successful programme to reduce poverty, food insecurity and inequality. Similar programmes are currently being adopted in other developing countries. However, a growing body of research reveals instances wherein which the programme has been less effective, even non-beneficial, and less is known about the environmental sustainability of the programme. In this paper we focus on a case study in three municipalities in the state of Minas Gerais. Based on in-depth interviews with local agricultural extension offices and a farmer questionnaire we quantify i) if participation in Zero Hunger and its core sub-programmes Bolsa Familia, PRONAF and PAA is influenced by the characteristics of farms and their households, ii) how such participation influences food security (overall food security, food access and self-sufficiency) and environmental sustainability (use of agro-chemicals and loss of natural vegetation) and iii) if farm and household characteristics mediate the impact of participation in Zero Hunger. We find evidence that Bolsa Familia targets younger, larger households with less land, while PRONAF and PAA targets younger farmers with more land and education. We find evidence that participation in certain Zero Hunger sub-programmes are associated with household food security, food access, food self-sufficiency and natural vegetation loss. However, the direction of association is mediated by household socio-demographic characteristics such as age and gender of head of household, household size and the amount received from other social security programmes. We find no consistent patterns of programme participation and agro-chemical (fertilizer and pesticide) use. We also identify the local agricultural extension offices as instrumental for farmers to participate and benefit from participation.

1. Introduction

Social protection programmes are a key strategy for influencing individual behaviour that, when rolled out at larger scales, can deliver significant improvements in social and environmental conditions (Barrientos, 2017; Devereux & Sabates-Wheeler, 2004). There is a clear need to target such programmes at groups of people that maximises programme effectiveness and cost efficiency. Agricultural programmes targeted at small scale farmers can be highly effective in reducing poverty and food security (World Bank, 2008) as despite being key food producers for rural and urban centres (Samberg et al., 2016) small-scale farmers often experience high levels of poverty and food insecurity (UNCTAD, 2015). Small-scale farmers are also a key target group for interventions that seek to enhance environmental protection. They typically live and farm in and around native vegetation, and their land-use decisions are key determinants of vegetation dynamics which can either support the persistence of native vegetation fragments (Perfecto et al., 2009; Perfecto & Vandermeer, 2010) or drive further fragmentation and loss of natural vegetation and biodiversity (Newbold et al., 2015; Tubiello et al., 2015).

Even social protection programmes that tend to target poor households often miss out on the poorest of the poor (Devereux, 2016; Schutter, 2013) which often includes small-scale farmers (UNCTAD, 2015). Even when participating, small-scale farmers do not always benefit from farm focused interventions especially when support from advisory services is limited (Jayne et al., 2014; Meyfroidt, 2018). Globally, one of the largest and apparently successful programmes that attempts to tackle multiple outcomes through influencing small-scale farmers is Brazil's Zero Hunger programme. Launched in 2003 with the aim of lifting 44 million poor Brazilians out of poverty and food insecurity (Silva et al., 2011), it has had a strong presence in rural areas where many poor families and small-scale farmers live (de Mattos & Bagolin, 2017). These groups form the main target population for Zero Hunger which consists of a range of sub-programmes. Bolsa Familia, the largest conditional cash transfer programme in the world, is aimed at poor families (not exclusively at small-scale farmers), and provide monthly cash conditional on child school attendance and family health monitoring (Leão & Maluf, 2013). Given primarily to a female household member the programme also aims to empower women (Paes-Sousa, et al., 2011). *The National Program to Strengthen Family Farming* (PRONAF) offers agricultural credit to small-scale farmers defined as family farmers, i.e. family run farms of less than four fiscal modules in size (one fiscal model being the area required to ensure economic viability of the farm, ranging from 5 to 110 hectares across Brazil depending on land quality (WWF-Brazil, 2016). PRONAF offers various credit lines targeted at particular populations (e.g. women and youth) or type of production (e.g. agro-ecology) (Guanziroli & Basco, 2010) and even has a credit-line called PRONAF-sustainable (Rocha, Burlandy, & Maluf, 2012). *The Food Acquisition Programme* (PAA), is targeted at family farmers and provides access for to price-controlled markets operated by state-linked institutions, e.g. local markets, government funded schools or other social assistance programmes

(Rocha et al., 2012). PAA also supports sustainable production practices, for instance by offering a higher price for organically produced food (Wittman & Blesh, 2017). Since 2009 PAA has been tightly linked to the *National School Feeding Programme* (PNAE), which provides free school meals to all children (Sidaner et al., 2013), and as a minimum 30% of all food distributed in schools has to be purchased from PAA (UNDP-IPC, 2013).

By combining direct cash and food relief with structural change interventions, the Zero Hunger programme follows an approach coined the Twin-track approach, believed to be instrumental behind the success of the programme (FAO, 2014). In fact, the Zero Hunger programme is considered to be the primary mechanism through which Brazil met the Millennium Development Goal of halving extreme poverty and hunger by 2015 (Castaneda, 2012). Individual sub-programmes have been found to increase farm incomes (Doretto & Michellon, 2007), food purchases in food insecure households (Agência IBASE, 2008) and reduce child malnutrition (Paes-Sousa et al., 2011) and infant mortality (Rasella et. al, 2013). Conversely, some case studies have found negligible and/or negative effects of sub-programmes on agricultural production, child malnutrition and long-term food security (Oldekop et al., 2015; Piperata et al., 2016; Thorkildsen, 2014). PRONAF in particular, but also other sub-programmes, have been criticised for sub-optimal targeting of those most in need of assistance. (Feijó, 2013; Soares, Ribas, & Osorio, 2010; UNDP-IPC, 2013). Moreover, it has been suggested that characteristics of less developed regions (e.g. low agricultural technology adoption), lack of supporting institutions and poor infrastructure reduce the effectiveness of Zero Hunger sub-programmes (Eusebio et al., 2016; Soares et al., 2010; UNDP-IPC, 2013). To our knowledge no studies have systematically looked for important mediating factors for programme effectiveness across multiple Zero Hunger sub-programmes, thus this is a key area of further research. In addition, there has been relatively few studies assessing Zero Hunger's impact on environmental sustainability. Most such studies have focused on the use of agro-chemicals and provide contrasting evidence. Participation in PAA has, for example, been found to reduce pesticide use (e.g. Cunha et al., 2017; Mesquita & Bursztyn, 2017; Wittman & Blesh, 2017), have no impact on pesticide use (Oliveira et al. 2017), and increase pesticide use (Chmielewska et al. 2010). Similarly contrasting effects have been reported for the impacts of PAA on inorganic fertiliser use (Chmielewska et al. 2010; Oliveira et al. 2017; Wittman & Blesh, 2017).

Investment in agriculture could either promote more efficient farming that enables individual land-owners to maintain or increase yields whilst retaining natural vegetation cover on their land, or promote expansion of the cultivated area at the expense of natural vegetation cover (Calaboni et al., 2018; Meyfroidt, 2018). We are only aware of one study that has assessed how a Zero Hunger sub-programme has influenced native vegetation. Thorkildsen (2014) found a reduction in farm land and a regeneration of Atlantic forest as a result of state cash and in kind transfers (including Bolsa Familia), however, this study was based on just one community living inside a protected area and is thus unlikely to be generally representative (Thorkildsen, 2014).

Here, we use social survey instruments to address key issues regarding participation in the Zero Hunger programme, and the effects of such participation on food security and environmental sustainability. These are key aspects of the sustainable development goals (Blesh et al., 2019). Whilst high quality environments can help to sustain long-term productivity of agricultural systems (Tscharntke et al., 2012), there are often trade-offs between food production and environmental sustainability (Meyfroidt, 2018). It is increasingly recognised that smallholders, i.e. the farmers targetted by Zero Hunger, are key actors that must be considered when managing such trade-offs (Liao & Brown, 2018; Meyfroidt, 2018). Specifically, we quantify i) if participation in Zero Hunger and its core sub-programmes is influenced by the characteristics of farms and their households, ii) how such participation influences food security (overall food security, food access and self-sufficiency) and environmental sustainability (use of agro-chemicals and loss of natural vegetation) and iii) if farm and household characteristics mediate the impact of participation in Zero Hunger. We do so using farmer questionnaires and structured interviews with local agricultural extension offices across three municipalities in the state of Minas Gerais, which lie within the highly threatened Cerrado and Atlantic Forest biomes (Myers et al., 2000).

2. Materials and Methods

Study area

Municipalities are the smallest administrative unit in Brazil and control much of the administration of Zero Hunger programmes. This study was conducted in Montes Claros, Ponte Nova and Ouro Verde (de Minas) municipalities in Minas Gerais in south-east Brazil (Figure 1). Minas Gerais is an ideal state to examine the effect of Zero Hunger on rural household food security and environmental sustainable practices. It has a long-history of high participation rates in Zero Hunger programmes (Chappell, 2018), and a similar agricultural composition to many other Brazilian states (Oldekop et al., 2015). The state is also of high environmental importance as it contains large components of the Atlantic forest and Cerrado biomes which are highly threatened global biodiversity hotspots (Myers et al., 2000) but continue to experience habitat loss and degradation (Beuchle et al., 2015; Joly et al., 2014; SOS Mata Atlântica, 2017). The three focal municipalities were purposefully selected as study sites given their location in these ecological biomes (Figure 1), their variation in aggregate development level (ranked in 2010 as 17th (Montes Claros) 138th (Ponte Nova) and 788th (Ouro Verde) out of the state's 853 municipalities; Atlas Brazil, 2013), and because all had at least 30 farmers participating in PAA (the sub-programme with the fewest participants) at the time leading up to data collection.

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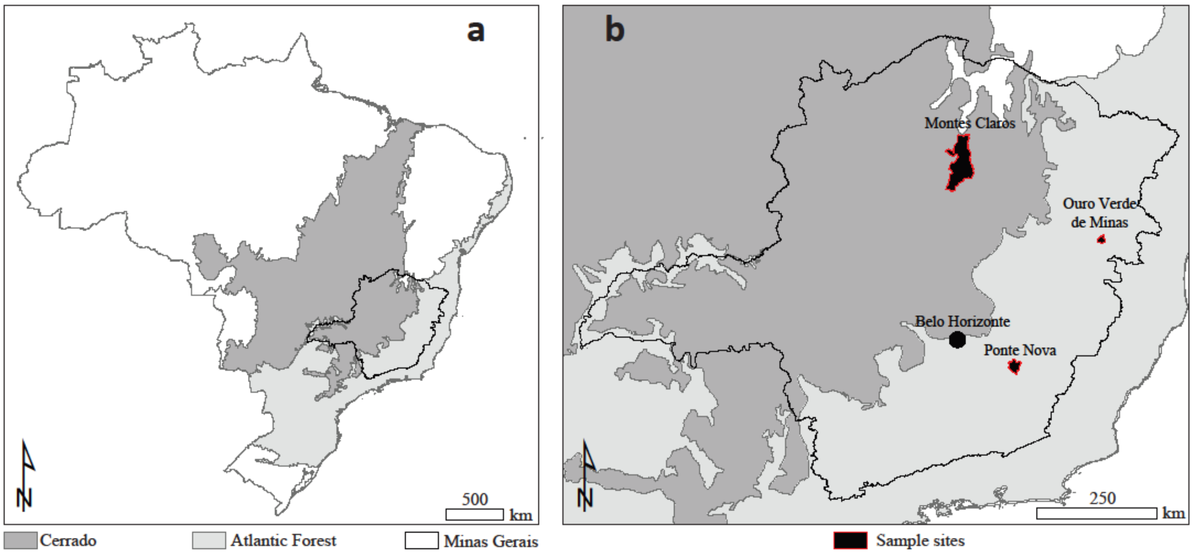

Figure 1. a Map of Brazil showing the Cerrado and Atlantic forest biome and the location of Minas Gerais state; **b** Map of Minas Gerais showing the location of the capital Belo Horizonte and the three study municipalities Montes Claros, Ouro Verde de Minas and Ponte Nova.

In all three municipalities the agricultural extension office *Enterprise for Technical Assistance and Rural Extension* (EMATER) provide agricultural assistance for family farmers and support their participation in PAA and PRONAF (but not Bolsa Familia). Due to spatial variation in the size of fiscal modules family farms are defined as ≤ 200 hectares in Ouro Verde, ≤ 160 hectares in Montes Claros and ≤ 104 hectares in Ponte Nova.

Sampling design

Data collection took place just before and during the rainy season (October 2016 and January 2017). In each municipality an initial in-depth interview with EMATER staff was carried out to understand the conditions and history of Zero Hunger and farming practices in each municipality and the layout of the municipality and farming communities. Farmers were subsequently recruited through a mixed targeted and snowball sampling approach to take part in a household survey; first, with the help of EMATER, current PAA participating households were targeted (to ensure we captured participants in this least-widespread programme), then with the help of the interviewed PAA farmer suitable nearby non-PAA participating farmers were identified, until a balanced sample was achieved in each municipality. In total 194 households took part in the survey, 70 (44% participating in PAA) in Montes Claros, 64 (49% participating in PAA) in Ouro Verde and 60 (43% participating in PAA) in Ponte Nova. A large number of respondents had also participated in the two other main Zero Hunger sub-programmes, i.e. Bolsa Familia and PRONAF, particularly in Ouro Verde (Table 1) and thus our analyses focus on the impacts of all three sub-programmes. The interviews were conducted face-to-face in Portuguese by one postgraduate researcher (CD) and two Brazilian research assistants. Handheld tablets and the Census and Survey Processing System (CSPro) software were used to administer the interviews.

Table 1. Survey respondent participation in the Zero Hunger programme in Montes Claros (MC), Ouro Verde (OV) and Ponte Nova (PN). Current participation reflects the number and proportion of survey respondents participating in the Zero Hunger sub-programmes Bolsa Familia, PRONAF and PAA in the past twelve months, and the number and proportion of respondents participating in any of the three programmes (for Zero Hunger). Current mean values reflect the average financial value received by participants in each sub-programme (in R$) and the average R$ received by participants from all programmes (for Zero Hunger). Total participation reflects the number and proportion of survey respondents who have participated in each sub-programme (for Zero Hunger in any sub-programme) at any point between 2003 and 2016. Total mean values reflect the average number of years participated (for Bolsa Familia and PAA) or the average total financial value received (from PRONAF) during this period. Mean total Zero Hunger reflects the average total number of programme years (i.e. the average sum of count of years of participation across all programmes).

		Current participation		**Total participation**	
	Municipality	*% (N obs.)*	*Mean (SD)*	*% (N obs.)*	*Mean (SD)*
Bolsa Familia	MC	33 (22)	R$ 1,570 (808)	62 (41)	7 yrs (4)
	OV	62 (39)	R$ 2,988 (3,321)	70 (44)	7 yrs (5)
	PN	15 (9)	R$ 1,570 (785)	40 (24)	7 yrs (4)
PRONAF	MC	12 (8)	R$ 1,815 (810)	76 (50)	R$ 22,386 (31,707)
	OV	27 (17)	R$ 5,378 (3,765)	79 (50)	R$ 30,412 (38,524)
	PN	8 (5)	R$ 3,467 (1,469)	33 (20)	R$ 57,661 (41,217)
PAA	MC	44 (29)	R$ 6,052 (5,068)	56 (37)	5 yrs (4)
	OV	49 (31)	R$ 7,469 (9,436)	62 (39)	5 yrs (3)
	PN	43 (26)	R$ 7,902 (6,493)	60 (36)	6 yrs (4)
Zero Hunger	MC	71 (47)	R$ 4,778 (4,936)	92 (61)	9 yrs (6)
	OV	84 (53)	R$ 8,292 (10,245)	97 (61)	10 yrs (6)
	PN	55 (33)	R$ 7,179 (6,665)	80 (48)	8 yrs (5)

Questionnaire design

Interviews were designed to capture information on two groups of outcome variables, i.e. food security and environmental sustainability. We obtained three measures of food security. First, *current household food insecurity* was calculated based on the FAO scale of self-reported food insecurity experience (Ballard et al., 2013). This uses eight questions capturing mild to severe food insecurity, such as "*during the last 12 months, was there a time when you were worried you would run out of food because of lack of money or other resources*" and "*during the last 12 months, was there a time when you went without eating for a whole day because of a lack of money or other resources*". These we adapted by asking for responses on a five point Likert scale (never, rarely, sometimes, almost always and always) instead of a binary yes/no response. To capture the whole household we asked about the general experience of household members. We followed the approach of many widely used scales (such as the Food Access Survey Tool (Na et al., 2015) and NR-6 nature relatedness scale (Nisbet & Zelenski, 2013)) and converted the Likert scale to a numerical score (0 = never; always = 4) and summed the scores across all eight questions to give an overall measure of current household food insecurity.

Second, food access is a main dimension of food security and refers to access in terms of both the quantity and quality of food (Ericksen, 2008). We captured data on *change in household food access* using three questions to capture these nuances, i.e. "since you have been managing the farm i) how has the amount of food your household has access to changed?, ii) how has the diversity of food your household has access to changed?, and iii) how has the amount of healthy and nutritious food your household has access to changed?", and coded responses on a 5 point Likert scale: much lower currently (coded as -2), a bit lower currently (coded as -1), no change (coded as 0), a bit higher currently (coded as +1) and much higher currently (coded as +2). We again summed the responses across these questions to give an overall measure of change in household food access. Third, we asked "*What is the proportion of household food consumption that comes from food produced on your farm?*"

We use this as a measure of *current food self-sufficiency* that captures information on a household's resilience to food insecurity as self-sufficiency reduces the impacts of regional or global factors that drive food price fluctuations or reduced market availability, although overreliance on home production, especially of a small number of products, can increase the risk of food insecurity due to local production failure (Krishna Bahadur et al., 2016).

We obtained two measures of environmental sustainability that captured data on agro-chemical usage, specifically inorganic fertiliser and pesticide usage in the past 12 months per hectare of farmed land. Fertiliser and pesticide use can promote biodiversity loss, increase pollution of soil, air and water and increase greenhouse gas emissions (Geiger et al., 2010; Vermeulen et al., 2012), and such negative impacts have been documented in the Atlantic forest and cerrado biomes (Hunke et al., 2015; Lopes et al., 2015). We quantify usage by total expenditure as data could not be obtained on application rates of active ingredients across the wide range of products used by respondents without substantially reducing survey participation due to the increased time required to conduct the survey.

Finally, due to the historically high and ongoing rapid loss of Cerrado and Atlantic Forest vegetation as a result of agricultural expansion (Beuchle et al., 2015; Joly et al., 2014; SOS Mata Atlântica, 2017) our third measure of environmental sustainability measures the amount of natural vegetation loss reported by participants. This included mature and secondary vegetation, which can both support substantial biodiversity and provide important ecosystem services (Barlow et al., 2007; Edwards et al., 2017). All losses were converted into hectares (ha), using conversion factors of 4.84 for Brazilian "alqueires" (a widely used standardised area unit in our survey region) unless respondents specifically specified otherwise. A small number of respondents reported clearing natural vegetation for planting eucalyptus trees but only reported the number of tree planted (we assumed that each tree resulted in the loss of $6m^2$ of natural vegetation - based on regional planting densities; EMBRAPA, 2018). In five cases change in land cover was recorded, however, a description of the original land cover was missing. In three of these the original land use prior to conversion was successfully established by examining historical Google Earth imagery of the property. In the other two cases historical Google Earth imagery was not available and these were thus excluded from the analysis. Natural vegetation loss between 2003 and 2016 occurred in just 16% of households (31 cases across 194 households) and the area lost was highly skewed (range: 0.0006 – 45 ha; median 3ha; mean 6 ha ± 3 (s.e.)). We thus converted this variable into an ordinal variable using natural breaks in its distribution, i.e. "None" (= 0 ha; n = 163), "Little" (> 0 to 1 ha; n = 15) and "High" (> 1 ha; n = 16). We express the variable in two ways: as natural vegetation loss from 2003-2016, and natural vegetation loss from the first year of household participation in each of the Zero Hunger sub-programmes (2003 for non-participants).

We quantify participation in Zero Hunger programmes in two ways. First, to represent current participation we capture the amount of money received from the three main Zero Hunger sub-programmes (individually and in total) in the 12 months prior to interview (expressed as R$ per 1000). Second, to represent total participation we capture the number of years since 2003 (when Zero Hunger started) that the household participated in Bolsa Familia and PAA, and the cumulative total value of PRONAF loans received (with the value for each year adjusted to 2016 equivalent values). For total Zero Hunger participation we calculate the sum of programme years, i.e. the number of years in which the respondent participated in each sub-programme. We also collected a wide range of socio-demographic variables that could either influence participation rates or our outcome variables (Table 2).

Table 2. Household variables and their rational for inclusion when assessing a) influences on participation in Zero Hunger (* indicates variables used in such analyses), and b) as predictor variables in models assessing Zero Hunger programme effects on household food security (defined as food insecurity, food access and food self-sufficiency), and environmental sustainability (defined as per hectare inorganic fertilizer and chemical pesticide use, and natural vegetation loss). Ref. indicates the reference level for categorical variables.

Variables	Rationale for assessing associations with participation	Rational for inclusion when modelling outcomes of participation
Gender household head* *(Female (ref.) and Male)*	Included to assess potential issues with gender equality associated with Zero Hunger participation.	Women often have less access to assets (IFAD, 2010) and increased likelihood of food insecurity (Felker-Kantor & Wood, 2012), though drive more favourable spending patterns for household food security than men (Ibid.), and provide important nutrients/income as main managers of home gardens (Galhena et al., 2013). Female-headed households are found less likely to clear forest (Babigumira et al., 2014).
Age household head* *(years)*	PRONAF participation could be restricted to younger farmers as they have more time available to pay back loans. More generally, younger farmers may be more interested in agricultural innovations promoted by Zero Hunger. Conversely, younger farmers often have less experience and weaker social status which can limit their access to credit (Babigumira et al., 2014; Mengistu et al., 2016) although PRONAF attempts to counter this with a credit line that is restricted to younger farmers.	Younger farm households are often ambitious and physically able to intensify or expand production (at the expense of natural vegetation), but often suffer from reduced experience-, assets- and financial base which can reduce food security and use of inputs (Babigumira et al., 2014; Mango et al., 2014; Mengistu et al., 2016). The stronger financial position of older households can generate higher social status and access to credit (Babigumira et al., 2014; Mengistu et al., 2016).
Ethnicity household head**(African desc.* (ref.)*, European, Mixed race)* Three Asian households were recorded but excluded as they caused unstable parameter estimation	In Brazil ethnic minorities often have less formalised land rights (Kepple et al., 2014) which may reduce willingness to obtain credit or invest in managing that land, and thus participate in Zero Hunger. Alternatively, as such groups are a key target population for social development informal or formal positive discrimination could increase participation rates.	In Brazil, indigenous and quilombo households (descendants from African slaves) have traditionally had higher poverty and food insecurity, although recently there have been attempts to improve their conditions (Kepple et al., 2014)
Education household head* *(total years of education)*	Included to assess potential issues with equality, and as better educated households may have access to literature promoting Zero Hunger or greater understanding of potential benefits of participation.	Households with higher education levels are likely to have access to information and capacity to enhance food security (Mango et al., 2014), increased off-farm opportunities and increased access to agricultural loans which can positively or negatively drive forest clearing (Babigumira et al., 2014), and are also more likely to adopt pro-environmental farming practices (Kibue et al., 2016).
Household size* *(household members that share resources)*	Larger households have greater access to labour (via family members) and thus may be in a better position to participate in the farm-related Zero Hunger programmes. If larger household size is driven by the number of dependent children these are also more likely to receive support from Bolsa Familia.	Family members are the main source of labour for most small-scale farmers (Lowder et al., 2016), although larger households also increase consumption pressure (Deressa et al., 2009).

Household poverty index *(Principal Component Analysis index*; see Table S1)	Whilst poorer households can have reduced access to development programmes (Schutter, 2013) we do not include here as participation is likely to influence poverty levels and data on poverty pre-participation is not available.	Poverty can have detrimental impacts on household food insecurity and agricultural practices by preventing the adoption of effective livelihood strategies (De Haan, 2012).
Log_{10} (Land area)* (owned and managed) *(total hectares)*	Included as larger farms may have greater capacity to take advantage of the opportunities provided by participating in Zero Hunger.	This can determine the amount of food produced and thus increase household food security (Rammohan & Pritchard, 2014), whilst potentially increasing the likelihood of natural vegetation loss (Babigumira et al., 2014). When controlling for household land area we match the area relevant for each model outcome, i.e. for food insecurity, food access and natural vegetation loss we control for land owned and/or managed as both can benefit food security and represent area for natural vegetation loss. For food self-sufficiency and chemical input use we only control for land managed by the household as this land is likely the only source of self-produce and destination of household input.
Property years* *(years of family on the farm)*	Amount of time spent farming the focal land may increase willingness to obtain credit or invest in managing that land, and thus participate in Zero Hunger. In addition, greater experience of the focal land may improve the chances of applications to participate being accepted.	This provides an index of farming experience in the local environment. Farming experience can positively influence food security (Mohammed et al., 2016; Onasanya & Obayelu, 2016), and is also associated with pro-environmental behaviour although the direction of effect is context specific.
Log_{10} (Farm expenses) *(total R$ in last 12 months)*	Not included as farm expenses are likely to be determined by PRONAF loans increasing the capacity for expenditure and increased income arising from Zero Hunger participation.	This provides an index of intensification, which can increase yields and thus food security, particularly for households with limited access to land (Dixon et al., 2001), whilst increasing local loss of natural vegetation it can reduce deforestation at a regional scale (Byerlee et al., 2014). Note that when modelling agro-chemical use expenditure on the modelled agro-chemical type is not included when calculating farm expenses
Log_{10} (Agricultural credit)* *(R$ 2003-2016)* non-PRONAF credit, (adjusted to year 2016)	Included as other sources of credit may reduce the need to participate in PRONAF.	Agricultural credit can enable small-scale farmers to gain access to the financial resources needed to produce efficiently and improve livelihoods, and is found to reduce rural poverty (Burgess & Pande, 2005), but credit access can also drive deforestation (Assunção et al., 2013)
Farm type* *(Crop dominant* (ref.), *Mixed* and *Pasture dominant)* Crop and pasture dominated farms defined as those with 95% area coverage by these crops (resulting in 67 crop farms; 83 mixed farms and 38 pasture farms).	Included to assess potential unequal capacity to benefit from Zero Hunger across major farm types (although this may be driven by differences across farming sectors in the perceived benefits of participation).	Farm type affects food security differently, e.g. livestock production in particular can be beneficial for household food security as a resource to sell during food shortages, draught power for farm activities and provide a range of foods for household consumption (Bogale & Shimelis, 2009). Mixed farming systems or diversified crop production are found particularly beneficial as a risk aversion strategy and support food security, as opposed to mono-crop farms which are particularly susceptible to shocks and pests (Krishna Bahadur et al., 2016).
Agricultural cooperative participation (current) *(No (ref.) and Yes)*	Not included as aspects of the PRONAF sub-programme require participants to be members of a co-operative.	Participation in an agricultural cooperative can increase access to equipment, inputs and markets, and uptake of new agricultural technologies, as well as increase livelihoods, although not always, and may also lead to negative environmental performance (Ahmed & Mesfin, 2017; Mojo et al., 2015; Verhofstadt & Maertens, 2015)

Agricultural training (household member) *(No (ref.) and Yes)*	Not included as participation in Zero Hunger requires engagement with EMATER offices which also promote participation in agricultural training.	Increased knowledge from agricultural training, often supplied by rural extension officers, can increase use of effective and sustainable technologies improving livelihoods and the environment (Kibue et al., 2016; Mango et al., 2014; Yila & Thapa, 2011)
Log_{10} (Other social protection)* *(R$ in last 12 months)*	Included as availability of other support may reduce the need to obtain benefits by participating in Zero Hunger.	Other social protection programmes, e.g. rural pension and disability, provide vital support for targeted rural inhabitants and can reduce poverty (Holmes et al., 2011).
Municipality* (*Montes Claros* (Ref.), *Ouro Verde* and *Ponte Nova*)	Included as variation in the effectiveness of EMATER offices or quality of relationships with key personal or institutions (such as banks offering PRONAF loans) could drive regional variation in participation.	These control much of the administration of Zero Hunger programmes and associated local institutions (Chmielewska & Souza, 2011) and also capture spatial variation in climate and geography. It is modelled as a fixed factor.

Lastly, we collect information concerning the mechanisms that may drive the observed changes and focal outcome variables. These questions include open-ended questions that obtain in depth information on mechanisms driving changes carried out in farming practices and land use and principal reasons for change in, or lack of, food access. In addition, for households which were currently or had previously participated in one of the three Zero Hunger programmes we probe into the motivation behind, and experience of, participation, in particular the mechanisms behind and specific outcomes of participation on food security and farming practices. The complete questionnaire is provided in the Thesis Appendix. Replies to the open-ended question were translated using R's "RYandexTranslate" package and translation verification and modification was conducted in consultation with a fluent Portuguese speaker (a Brazilian native) who was familiar with phrases used by residents in our focal study area. Responses were then uploaded to a RQDA database provided by R's "RQDA" package, and used to add detailed qualitative information to help explain the results of the statistical analysis described below.

Statistical analysis

All analyses were conducted in R version 3.4.2.

First we test for associations between Zero Hunger participation and respondents' geographic, demographic and socio-economic characteristics (see Table 2 for list of characteristics and rationale for inclusion). The results of these analyses are used to determine participation patterns and, in part, to assess if results from the models of how Zero Hunger programmes influence food security and environmental sustainability are biased due to non-random participation, commonly referred to as *selection bias*. Given our relatively small sample size and lack of pre-treatment covariates, alternative methods to deal with selection bias such as propensity score matching or weighting are less appropriate (E. a. Stuart, 2010). These analyses are conducted considering current participation (defined as within the 12 months prior to the interview) and total participation (defined as at any point since 2003) in any aspect of Zero Hunger, and separately for the main three sub-programmes that we consider (i.e. Bolsa Familia, PRONAF and PAA). Analyses of continuous variables are conducted using two-sided T-tests and the "stats" package. Due to skewed distributions caused by a few large outliers four variables (land area, farm expenses, non-PRONAF agricultural credit and non-Zero Hunger social protection) are $\log_{10}$ transformed (when necessary after adding a constant of half of the minimum non-zero value to deal with zero values) prior to analysis. Analyses of categorical variables are conducted using Chi-squared tests (also in the "stats" package), and we compute *P*-values using a Monte Carlo simulation (with 2000 replicates).

We then model food security and environmental sustainability outcomes as a function of participation in Zero Hunger programmes (separately and in total) whilst controlling for the confounding variables listed in Table 2. The only exception being for the natural vegetation models where non-PRONAF agricultural credit had to be excluded due to problems with perfect separation. For each outcome variable we construct full models using all the covariates listed in Table 2 and assess the significance of Zero Hunger participation parameter estimates. For outcomes expressing current conditions (food insecurity, food self-sufficiency and use of chemical inputs) we assess the significance of current programme participation and total participation in separate models. For outcomes which are long-term in nature (change in food access and removal of natural vegetation) we only assess the influence of total participation. To isolate the effect of current participation on our outcomes we control for previous programme participation.

In addition, to isolate the effect of each Zero Hunger sub-programme we control for participation in the other sub-programmes. For example, when modelling the effect of current Bolsa Familia participation on household food insecurity we control for previous Bolsa Familia participation, current participation in PAA and PRONAF (combined) and previous participation in PAA and PRONAF (combined). In all models Variance Inflation Factors are less than five and our results are thus not unduly influenced by multicollinearity. In all models we include eight two-way interactions between Zero Hunger participation and other predictor variables when there is a plausible hypothesis that such interactions could moderate the influence of Zero Hunger (Table 3). These interactions are modelled sequentially by adding a single interaction in turn to the full model that only includes main effects. We retain any interactions terms for which $P < 0.05$.

Table 3. Two-way interactions between Zero Hunger participation and other predictor variables included in regression models, and the hypothesis for inclusion

Interaction	Hypothesized moderating influences on the impact of Zero Hunger participation
Gender household head	Male and female spending patterns can have different impacts, for example female spending is more likely to promote household food security (Felker-Kantor & Wood, 2012) thus increasing Zero Hunger impact
Age household head	The majority of rural people start farming when young, thus age can serve as a proxy for farm experience. Higher farm experience may increase adherence to Zero Hunger farm related requirements and result in increased benefits of participation
Household size	PRONAF and PAA participation might be more effective in larger households because the available (family) farm labour is higher
Land area	Zero Hunger could vary in effectiveness between small and large farms because, even if Zero Hunger participation increases farm production and/or income from farming on small farms the magnitude of increase might be insufficient to improve food security. As an example, yield increases on small farms (size 0-5 ha) were insufficient to deliver poverty alleviation in Brazilian dry-lands (Helfand et al., 2015). Similarly, there may be more pressure to increase yields on small farms through increased use of agro-chemicals or removal of natural vegetation to increase the farmed area.
Farm type	Farm type is a fundamental characteristic of farm households. Farm types (arable, mixed and livestock) could benefit differently from Zero Hunger participation because the type of food produced and markets accessed as a result of Zero Hunger participation likely varies by farm type and subsequently likely have different impacts on food security, self-sufficiency and chemical inputs.
Agricultural coop. part.	Participants in an agricultural cooperative might be able to benefit more from PRONAF and PAA since the cooperative could provide access to labour or equipment that increases clearance

	of natural vegetation, or the range of potential farming methods (including changing chemical use) or other more effective uses of the increased income/credit.
Agricultural training	Farmers with agricultural training could benefit more from Zero Hunger as they might apply more effective farm practices following receipt of Zero Hunger income/credit. If training is focused on sustainable practices it might also influence reduced chemical input use (Kibue et al., 2016; Mango et al., 2014; Yila & Thapa, 2011)
Social protection	Households with simultaneous income from other non-Zero Hunger social protection programmes could be more able to effectively use Zero Hunger income given that many of these other cash transfers are relatively large and are received regularly (e.g. rural pension or disability) (Osorio et al., 2011)

Food access and food self-sufficiency were normally distributed and were thus modelled using ordinary least square (OLS) models constructed using the “stats” package. Our food insecurity outcome variable was over-dispersed, with a quasi-poisson model providing a better fit to the mean-variance structure than a negative binomial model (tested by plotting the the quasi-poisson and negative binomial model against the mean-variance of the outcome variable; following Ver Hoef & Boveng 2007). Quasi-poisson models were thus fitted with a log link in the “stats” package. Our outcome variables measuring inorganic fertiliser and pesticide use were highly skewed and included an over-representation of zeros (97 and 57 of 186 cases). We thus construct two-step hurdle models and modelled the likelihood that farmers used fertilizer and pesticides using a generalized linear binomial model with a logit link (“stats” package). We then modelled the non-zero responses (following $\log_{10}$ transformations) using OLS models. Note that when including farm costs as a predictor in these models we calculate farm costs excluding the costs of the agro-chemical type used as the outcome variable.

Natural vegetation loss overall (2003-2016), and natural vegetation loss since the first year of Zero Hunger programme participation, were modelled using Ordinal regression with a logistic link using R’s “MASS” package. Initial models received warnings of prefect separation caused by low occurrences of loss and few households with agricultural credit (all households with credit had no removal of natural vegetation). Whilst agricultural credit has been found to drive natural vegetation loss (Assunção et al., 2013) this contrasts with the pattern in our data and due to the issues of unstable parameter estimates and that few households received agricultural credit (other than PRONAF) we exclude this covariate from our natural vegetation loss models. These models included all the other confounding variables listed in Table 1 as predictors. Descriptive statistics for all dependent, treatment and confounding variables are provided in Table S2.

Final model sample sizes ranged from 185 to 190 observations, with observation exclusions due to lack of outcome information (chemical inputs and removal of natural vegetation), treatment information (PRONAF) or covariate information (agricultural training). We conduct a post-hoc power analysis to assess the ability of our models to detect effects. For the food access and food self-sufficiency models the likelihood of detecting medium effect sizes (defined as 0.15; Cohen, 1988) is above 80%. For the truncated fertilizer and pesticide models the likelihood of detecting large effects (defined as 0.35; Cohen, 1988) is above 80% and notably we do detect effects of Zero Hunger participation in these models. Robust methods for conducting power analyses for multi-variable Quasi-Poisson, binomial (logistic) and ordinal models are not yet available, and methods for models using multiple predictors require making quantitative assumptions derived from theory that is not sufficiently developed for our study system – power analyses were thus not conducted for these models that assessed food insecurity, use of agro-chemicals, and loss of natural vegetation. We do, however, detect some effects of Zero Hunger participation on these outcome variables suggesting that our analyses are not unduly influenced by insufficient power due to somewhat limited sample sizes (189 respondents).

3. Results

Differences between participants and non-participants

Total participation rates in Zero Hunger and Bolsa Familia, PRONAF and PAA sub-programmes (defined as participation at any point since 2003) were not associated with the head of household's gender and education level, but were associated with head of household's age and ethnicity, household size, farm type, size of the farm, amount of time spent farming the site, and the amount of money received from other agricultural credit or social protection programmes and municipality (Table 4). Current participation rates (defined as participation within the last 12 months of interview) showed fairly consistent patters, the major differences being that PRONAFparticipation was no longer associated with farm type (Table S3).

Younger households were more likely to participate currently in all Zero Hunger programmes, while younger households were also more likely to have participated at any point in Zero Hunger and Bolsa Familia. Here PAA participants exhibited a similar but non-significant trend. More educated households were likely to participate currently in PAA. A similar but only marginally significant trend was found for households participating in PAA at any point, and for households participating currently or at any point in PRONAF. European descendant households were more likely to participate in PAA currently. Mixed-race households were more likely to have participated in overall Zero Hunger and Bolsa Familia since 2003, and participants in these programmes were also more likely to have a larger family size. The probability of participation in PRONAF (at any point) was highest for households with mixed farms and lowest for crop farming households; participation in PAA (at any point) exhibited a non-significant trend to be highest for mixed farms and lowest for pasture farms.

Smaller farms were more likely to participate in Bolsa Familia currently and at any point since 2003, but less likely to have participated in PRONAF. Current participation in PAA is also negatively associated with farm size, and PAA participation at any point since 2003 show the same trend (although the trend is not significant). We note, that of total farms with a farm size of 2 hectare or less (i.e. the common global definition of a small-scale farmer) only 35% had received a PRONAF loan at any point (14% had a loan in the last 12 months) while only 38% had participated in PAA at any point (27% participated in the last 12 months). Farmers who had spent less time on their farm were more likely to participate in Bolsa Familia currently and at any point since 2003.

Households who received larger amounts of agricultural credit (excluding that from PRONAF) were more likely to participate in Zero Hunger (at any point) and PAA (currently and at any point). Conversely, farmers that received more money from other social protection programmes were less likely to have participated in Zero Hunger, Bolsa Familia or PAA. The equivalent trend also influenced current participation in Zero Hunger overall and for Bolsa Familia. Geographical location also influenced both total and current participation rates with respondents in Ponte Nova having lower participation rates in overall Zero Hunger, Bolsa Familia and PRONAF than participants in Ouro Verde and Monte Claros. Participation rates in PAA did not differ significantly across municipalities.

Table 4. Average demographic and socioeconomic characteristics for sampled households, and mean differences in participation (defined as participation at any point since 2003) within Zero Hunger overall-, and the Bolsa Familia, PRONAF and PAA sub-programmes. For the categorical variables instead of mean values and differences we report the proportion of respondents that participate for each level of the categorical variables. Significance levels for continuous variables are based on Two-Sample T-tests while for categorical variables on Chi-squared tests: # *P* < 0.1; * *P* < 0.05; ** *P* < 0.01; *** *P* < 0.001. Reals (R$) is the Brazilian currency; £1 is approximately 5 R$

		Mean differences Participant vs. Non-Participant			
Variables	***Mean (SD) all respondents***	*Zero Hunger*	*Bolsa Familia*	*PRONAF*	*PAA*
Head of household (HH) gender (male/female)		Male 91% participate Female 80% participate	Male 59% participate Female 50% participate	Male 65% participate Female 50% participate	Male 60% participate Female 55% participate
HH age (years)	53 (14)	-9.53**	-9.84***	-2.69	#-3.92
HH education level (school years)	5.07 (3.72)	-0.8	#-1.24	#0.76	#0.91
HH ethnicity (African descendant., European, Mixed race)		* African 79% participate European 89% participate Mixed 94% participate	** African 48% participate European 40% participate Mixed 68% participate	African 58% participate European 62% participate Mixed 66% participate	African 55% participate European 68% participate Mixed 57% participate
Household size (members)	3.51 (1.47)	0.86**	1***	-0.13	-0.21
Farm type (Crop, Pasture and Mixed)		Crop 87% participate Pasture 84% participate	Crop 63% participate Pasture 53% participate	** Crop 47% participate Pasture 66% participate	# Crop 59% participate Pasture 45% participate

		Mixed 95% participate	Mixed 55% participate	Mixed 76% participate	Mixed 66% participate
Land size (ha)	19 (40)	1.72	-19.29***	4.88***	#2.59
Property years	24 (15)	0.46	-7.39**	1.42	0.92
Agricultural credit (total R$)	1,548 (8,037)	1,721***	410	1,680	2,376*
Other social protection (annual R$)	9,536 (15,379)	-15,972**	-12,695***	-3,297	-5,924*
Municipality (Montes Claros, Ouro Verde and Ponte Nova)		** MC 92% participate OV 97% participate PN 80% participate	** MC 62% participate OV 70% participate PN 40% participate	*** MC 76% participate OV 79% participate PN 33% participate	MC 56% participate OV 62% participate PN 60% participate
Sample size (participant / non-participant)		170 / 19	109 / 80	120 / 69	112 / 77

Note* for Land size, Agricultural credit and Other social protection the variables are log10 transformed prior to statistical tests but mean differences reported are raw (untransformed) values

Food security and programme participation

Food insecurity

The total amount of money received through PRONAF was marginally positively associated with food insecurity (Table S4, model 6: coefficient 1.43; $P = 0.07$), thus suggesting an increase in food insecurity, but this effect was significantly moderated by household size with the slope of the relationship being reduced in larger households (interaction term coefficient -0.54; $P = 0.02$). Food security was not related to any other measures of total or current participation or the interactions between participation and other predictors.

Change in food access

The number of years in which households participated in Zero Hunger was associated with increased access to food (Table S5, model 1: coefficient 0.59; $P = 0.04$; model 2: coefficient 0.13; P = 0.04), with evidence that these associations were negated when household heads were male (Table S5, model 1: interaction term coefficient -0.38; $P = 0.004$) or households were part of a co-operative (Table S5, model 2: interaction term coefficient -0.15; $P = 0.04$). Similarly, the number of years participation in Bolsa Familia was positively associated with access to food (Table S5, coefficient: 0.43; $P = 0.04$) but this association was negated when household heads were male (Table S5, interaction term coefficient: -0.45; $P = 0.03$).

Descriptive information about self-expressed effects of Bolsa Familia participation on food access support the statistical result. Here we find that a higher proportion of female headed compared to male headed households reported that access to food had increased as a result of Bolsa Familia participation; 20% reported a high increase in the quantity of food, 20% a high increase in the diversity, and 40% a high increase in the health of the food, compared to only 11%, 7% and 7%, respectively, of male-headed households. When asked to describe why, one female-headed household respondent stated: "*It (Bolsa Familia) was the only income*" [Interview 3, Ouro Verde], while another explained: "*It is used to buy nutritious food for the children, for instance milk or… fruit. Before the income was not sufficient. It helps a lot*" [Interview 52, Ponte Nova]. We note, however, that from the households reporting no change in food access as a result of Bolsa Familia (37-43% of total Bolsa Familia participation sample), we were commonly told the money received was rather used to cover other expenses such as clothes, shoes or school supplies for children. This could suggest that their food needs are already met or that it is seen as a more important investment. This again could be influenced by Bolsa Familia seeing that the programme focuses heavily on increasing school attendance amongst participating families.

The number of years of participation in PAA was negatively associated with change in food access (Table S5, model 5: coefficient -0.56; $P = 0.02$), but the slope of this relationship became increasingly shallow when participants were older and the relationship becomes positive for the oldest participants (Table S5, model 5: interaction coefficient 0.01; $P = 0.0005$). The number of years of participation in PAA has a negligible influence on change in food access in a competing model (Table S5, model 6: coefficient -0.03; $P = 0.75$) but a marked positive interaction with the amount of money received through other social protection programmes (Table S5, model 6: interaction coefficient +0.20; $P = 0.03$).

Additional survey information regarding PAA farmers experience with the programme sheds more light on the significant associations described here. The positive association with age appears linked to the ability of farmers to adhere to the programme requirements. When asked about their experience older farmers (age 30-70) reported they found it much easier compared to younger farmers (<30 years) to produce and deliver the right amount of food at the right time (Figure 3).

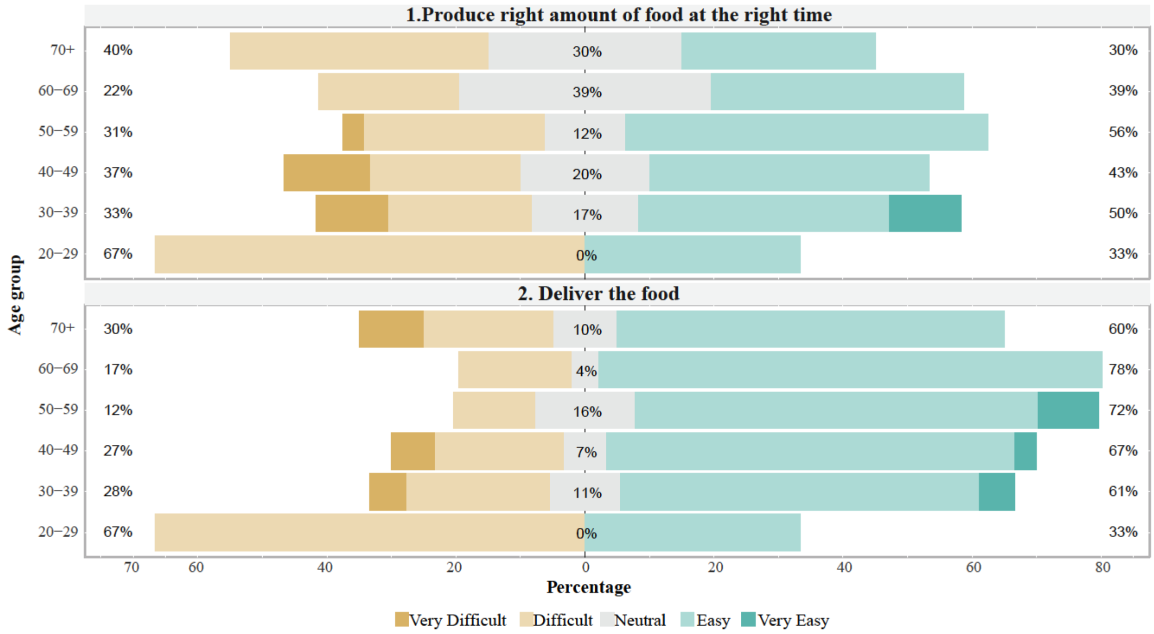

Figure 3. PAA participating farmers experience of producing and delivering food to PAA, showing proportion of negatively loaded replies (very difficult and difficult), positively loaded replies (easy and very easy), and neutral replies, by age groups 20-29, 30-39, 40-49, 50-59, 60-69, and 70+

The significant positive association with other social protection benefits suggests that when households also receive other cash-transfers the effectiveness of PAA is higher than it otherwise would be. Many respondents complained about the irregularity of PAA payments. In addition, overall 62% of PAA participating households replied they were not selling as much produce to PAA as they would like. This suggests that their level of participation is below their production capacity. With an average value received from PAA of R$ 7,718, which represents 20% of their average gross income, this is also well below the the maximum annual allowed value of R$ 24,000 (UNDP-IPC, 2013) suggesting that from the supply side there is scope to increase participation.

Food self-sufficiency

Participation in overall Zero Hunger or Bolsa Familia was not associated with self-sufficiency (the proportion of household food consumption that was produced on the farm). The amount of money currently received from PRONAF was negatively but non-significantly associated with self-sufficiency (Table S6, model 5: coefficient -9.31; P = 0.16) but interacted positively with farm area (Table S6, model 5: interaction coefficient 12.57; P = 0.02) such that participation increased self-sufficiency for the largest farms. The total amount of money received from PRONAF was positively but non-significantly associated with self-sufficiency (Table S6, model 6: coefficient 9.09; P = 0.14) but interacted negatively with household size (interaction coefficient -3.20; P = 0.05) such that the largest households had lower self-sufficiency when they received more PRONAF money.

Farmers with larger farm areas are likely more able to diversify production which supports increased food self-sufficiency, e.g. facilitate crop and livestock mixed farming systems. Additional survey information show that for a majority of PRONAF participants, participation has led to increased variety of production as well as an increased overall production (Figure 4).

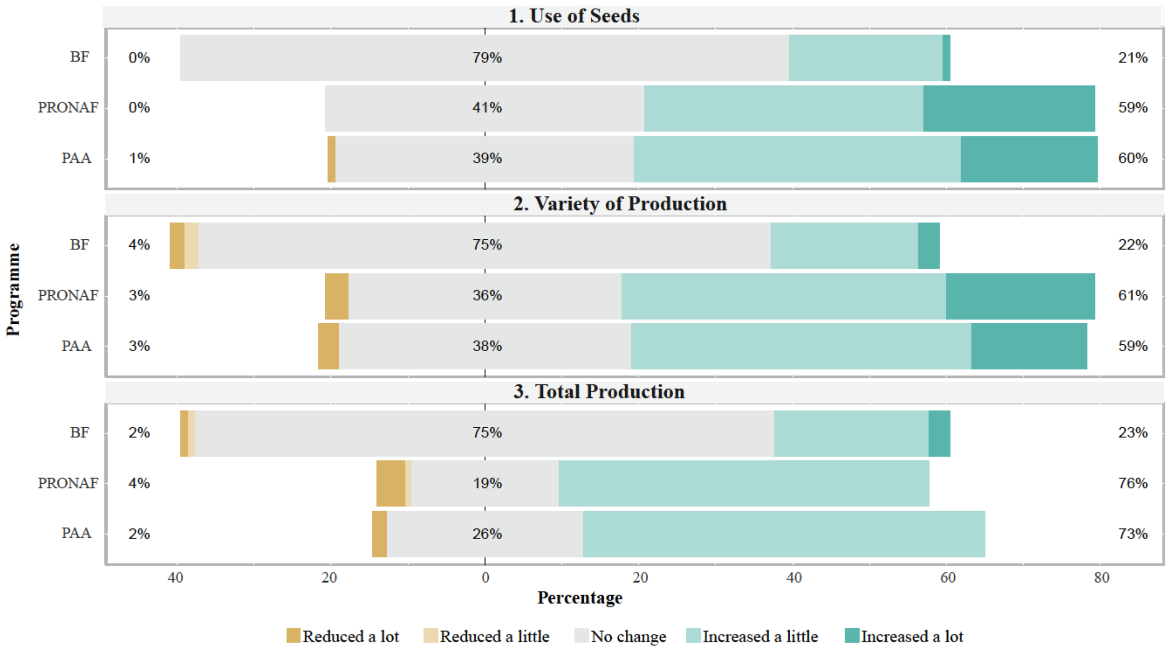

Figure 4. Self-reported impact of programme participation on farming practices (use of seeds, variety of production and total production), showing proportion of negative impact (reduced a lot and reduced a little), neutral replies , and positive impact (increased a little and increased a lot), by main Zero Hunger sub-programmes Bolsa Familia (BF), PRONAF and PAA

A competing PRONAF model (Table S6, model 7) found that total amount of money received through PRONAF was negatively associated with self-sufficiency (coefficient -6.62; P = 0.06), but interacted positively with the amount of other social protection money that was received (coefficient 7.07; P = 0.03). The amount of money currently received through PAA was also negatively associated with self-sufficiency, albeit with marginal significance (Table S6; model 8: coefficient -6.83; P = 0.06), and also interacted positively with the amount of money received through other social protection programmes (Table S6, model 8: interaction coefficient 7.25; P = 0.05). Similar patterns occurred with regard to the total amount of money received from PAA (Table S6, model 9: participation coefficient: -0.03; P = 0.96; interaction coefficient: 1.44; P = 0.03).

Environmental sustainability and programme participation

Use of agro-chemicals

Expenditure on inorganic fertilizer and pesticide was highly skewed and we thus assessed how participation was associated with the use of these chemicals, and then the amount spent on them amongst households that used them.

The probability of using inorganic fertilizer was higher amongst farmers that currently received more money from Zero Hunger (Table S7, model 1: coefficient 0.59; P = 0.04) but this effect was reduced when households received agricultural training (Table S7, model 1: interaction coefficient -0.89; P = 0.03). The only other significant main effect association between participation and probability of inorganic fertilizer use was increased likelihood when households participated more regularly in Bolsa Familia (Table S7, model 7: coefficient 0.49; P = 0.04) but this significant effect was not detectable in other specifications of the same model (Table S7, models 6 & 8). Models detected a number of significant effects of interactions between participation and other predictors but these were rarely consistent when measuring participation as current or total participation (Table S7). The amount of inorganic fertilizer used was negatively associated with the amount of money that was currently received from Zero Hunger (Table S9, model 1: coefficient -0.40; P = 0.03) but there was a positive interaction between participation and male head of households (Table S9, model 1: interaction coefficient 0.46; P = 0.02). No other measures of participation in Zero Hunger or its sub-programmes, or interactions between participation and other predictors, were significant (Table S9).

The probability of using pesticides was negatively associated with current income from Zero Hunger (Table S8, model 1: coefficient -0.60; P = 0.048; model 2: coefficient -0.59; P = 0.07) but interacted positively with membership of a co-operative (model 1: interaction coefficient 0.91; P = 0.01) and land area (model 2: interaction coefficient 0.58; P = 0.03). In contrast, the number of years that a respondent had participated in Zero Hunger, since the first year of participation, tended to be positively associated with the probability of using pesticides (Table S8: model 3: coefficient 0.20, P = 0.08; model 4: coefficient 0.18, P = 0.04) albeit with negative interactions with male head of households (model 3, interaction coefficient -0.23, P = 0.04) and household size (model 4, interaction coefficient -0.06, P = 0.02). There were no consistent patterns between participation in other Zero Hunger sub-programmes and the probability of using pesticides (Table S8). Amongst those farmers that used pesticides there was negligible evidence that participation in zero hunger increased the amount that was used (Table S10).

Additional survey information on Zero Hunger sub-programme participants' experience and use of agro-chemicals reveal two competing underlying drivers. On the one hand, there is a current focus to produce food free from agro-chemicals. Several farmers mentioned, for instance, the requirement of PAA of using less inputs. In the words of one farmer: "*It (participating in PAA) changed the variety and quality of products…In order to deliver to PAA you have to produce varied and higher* *quality food. But for me the main reason to produce with better quality (less chemical inputs) is because I am thinking about the people that will eat my products and it should be as good quality and healthy as if I were to eat it myself*" [Interview 40, Ouro Verde]. In fact, everyone we talked to who elaborated on their decision to use less inputs mentioned a human health concern, as opposed to an environmental concern, as the driving motivation. We found that the agricultural extension office EMATER was particularly influential in encouraging farmers to use less agro-chemicals. In fact they had an explicit institutional aim of increasing agro-ecological production amongst small-scale farmers. On the other hand, for many farmers there is still a need to use some agro-chemicals to be able to get an output. As one farmer explained: "…*you always have to fertilize…if you don't nothing will grow, but now people are more concerned about the quality (health) of the food*" [Interview 44, Montes Claros]. The self-expressed effect of Zero Hunger sub-programmes on the use of inputs we find is low, with only 3%, 28% and 27% of programme participants stating their use of chemical inputs has increased as result of participation in Bolsa Familia, PRONAF and PAA, respectively, and only 4% of PAA participants stating they have had any reduction in their chemical input use as a result of participation (Figure S1).

Loss of natural vegetation cover

Households that had participated in Bolsa Familia for more years were likely to have lost more natural vegetation if they received larger amounts of money from other social protection programmes (Table S11, model 3: participation coefficient -0.38, P = 0.47; interaction coefficient 1.17, P = 0.04). However, when restricting natural vegetation loss records from the first year of Bolsa Familia participation this interaction effect goes away. Rather, the number of years that a respondent participated in Bolsa Familia was positively associated (although with marginal significance) with the amount of natural vegetation lost from their farm (Table S11, model 4: coefficient 2.02; P = 0.09) and participation interacted significantly with household size with the strength of the relationship between participation and vegetation loss being reduced on larger farms (interaction coefficient -0.7; P = 0.04).

Respondents that had participated in PAA for more years were likely to have lost less natural vegetation when they had also received agricultural training (Table S11, model 7: participation coefficient -0.06, P = 0.53; interaction coefficient -0.36, P = 0.03). However, when restricting natural vegetation loss records from the first year of PAA participation this interaction effect goes away. The main association between the number of years that a respondent participated in PAA and natural vegetation lost from their farm remains negative i.e. suggesting PAA participation has not had any adverse effects on natural vegetation loss (Table S11, model 8: coefficient -0.23; P = 0.02).

In fact when asked directly, only 17% of PAA participants replied that participation had resulted in an increase in farm area (note, this increase could also have come from renting or purchasing already existing farm land) (Figure S1). Additional survey information revealed that the awareness of environmental laws was relatively high in all municipalities. Moreover, 58 respondents (31% of sample) reported that an environmental law had influenced their farming decisions, 28 respondents (15% of sample) also specified that deforestation laws had kept them from cutting down trees. We subsequently had low reported cases of natural vegetation loss. Environmental monitoring was also noticeable, and nine farmers mentioned specifically that they refrained from doing an illegal activity out of the fear of being fined. We also spoke to individuals who had been fined for deforesting or breaking other environmental laws. It is possible that these factors have contributed to the low occurrence of natural vegetation losses, though we recognize that due to the sensitive topic, some farmers might also have withheld information from us.

4. Discussion

We find that participation is influenced by a number of demographic and socio-economic factors that inform discussions of the effectiveness of targeting Zero Hunger programmes towards participants that are most in need of support. We question whether the PAA and PRONAF sub-programmes are reaching their intended target seeing that those who do participate are more likely to be more educated and have more land area. In fact, only about a third of farms of 2 hectare or less have participated in PAA or PRONAF at any point. Similar trends in participation are found in other studies (Chappell, 2018; Chmielewska & Souza, 2011; Eusebio et al., 2016). Though we recognize that our sample is not representative of overall farm participation (i.e. our sampling were not random), this suggests that the poorest most in need farmers are not being effectively targeted, opposite to the aim of the "productive inclusion" axis stated by the Ministry of Social Development and Fight against Hunger (MDS) (UNDP-IPC, 2013). To increase participation of the smallest farmers' local agricultural extension offices could prove instrumental. They have been found important for farmers in requiring the documentation for PRONAF and PAA that proves they are family farmers (often difficult for poor and uneducated farmers to do on their own). Local extension offices have also been found to increase participation in both PRONAF and PAA (Garcias & Kassouf, 2016; Nehring & McKay, 2013).

The participation patterns we find indicate that selection bias (Stuart & Rubin, 2007) may contribute to some of the associations that we document between participation and our focal outcome variables. Although our analyses take the influences of demographic and socio-economic factors and their interactions into account we are thus cautious regarding inferring causality of relationships when we document associations between participation and our outcome variables. Considering that many small-scale farmers in the developing world, particularly in African countries, are of 2 hectare or less (Jayne et al., 2014) and that farm interventions have been found less effective for particularly smaller farms (Meyfroidt, 2018), this also puts into question whether, when implemented in countries with predominately small farm sizes, programmes such as PAA and PRONAF will be able to deliver on on outcomes the same way as found in this research.

Close to all of our statistical models reveal that Zero Hunger and sub-programmes is mediated by a range of demographic and socio-economic characteristics. PRONAFs’ associated reduced food insecurity in larger households is likely explained by a higher ability of these households to take full advantage of the programme because they have more available family farm labour. Small-scale farmers rely primarily on family labour for their production. An overall trend of out-migration from rural areas, particularly by younger people (Zago, 2016), has led to labour shortages many places. We were told of this issue by several respondents, and are aware of similar issues in other municipalities in Minas Gerais (Oldekop et al., 2015). Incentivising individuals or groups of farmers to invest PRONAF credit in labour-reducing technologies can reduce farmers’ reliance on manual labour and enable them to produce and benefit more efficiently. In fact, Eusebio et al. (2016) found PRONAF to be the most efficient in areas with high technology adoption.

Our results suggest that Zero Hunger (and in particular Bolsa Familia) is only positively associated with increased access to food in female headed households. In male headed households the association is negative. Gender differences in rural Brazil and elsewhere are well reported, and suggest that female spending patterns are more favourable for household food security (Felker-Kantor & Wood, 2012; IFAD, 2010). Bolsa Familia actually pays special attention to women, and the cash-transfers are distributed primarily to a female household member (Paes-Sousa, et al., 2011) even when the head of household is male. Our results are thus rather surprising as they seem to suggest that despite the cash-transfer being given to females, the head of household still has a say in how money is spent, which ultimately appears to drive a less favourable outcome.

We find that the age of head of household mediates the slope of the associated relationship between PAA participation and change in food access. Particularly, whereas there is a negative association for younger participants there is a positive association for the oldest participants. A higher proportion of older participants also expressed an increased ease in adhering to programme requirements compared to younger participants. Older farmers might find it easier (or be more capable) to adhere to requirements due to their general higher farm experience and asset base (Babigumira et al., 2014; Mango et al., 2014). Other studies have identified a complex inscription process and irregularities in payment and delivery requirements as main hindrances of effective participation (Oldekop et al., 2015). Difficulties in transporting produce, found especially challenging in poorer areas with inadequate infrastructure, has also been identified (UNDP-IPC, 2013). It is thus likely that the often reduced capital and experience of younger farmers (Mengistu et al., 2016) make them less equipped to deal with these hindrances and keep them from benefitting. Shifting the burden of responsibility away from the individual to the collective could be a solution to minimize some of these hindrances. For instance, parts of PAA already incentivises individual farmers to work together in groups such as local cooperatives and associations (UNDP-IPC, 2013). Establishing a specific modality for younger farmers could also provide the needed additional support, as has already been done in PRONAF through the “*PRONAF-Jovem*” (i.e. PRONAF-young) credit line (Guanziroli & Basco, 2010). A modality targeted at young farmers might also increase their participation in the programme and if able to provide a viable livelihood, reduce the current out-migration of young people from rural areas (Cunha, et al., 2017; Mesquita & Bursztyn, 2017) and reduce the problem of farm labour shortages. For instance, only 6% of our sample are farms were with head of households of 30 years or below.

We also find that the associated relationship between PAA participation and change in food access is mediated by the amount of money received through other social protection programmes. Specifically, if the household also receives support from other programmes the positive effect of PAA is markedly higher the higher. The same relationship and interaction is found between PAA participation and food self-sufficiency, and PRONAF participation and food self-sufficiency. A plausible explanation for this is that the amount or frequency of PAA and PRONAF payments is insufficient for these households to make optimal farm decisions. For instance, the annual amount received from PAA participation per household in our study area (on average R$ 7,718) is considered low if one considers that it only represents 20% of the average gross annual income. This amount is also low compared to the legally set maximum allowance of R$ 24,000 per annum (UNDP-IPC, 2013). We find that there is both additional available supply and demand for PAA produced food, i.e. 62% of PAA participating households would like to sell more produce through PAA, and schools in the area purchase at maximum 30% food needed for their school meal programme through PAA. Most PAA and PRONAF payments were also not very regular (e.g. monthly) but payed out either per 6 months or annually (PAA), while PRONAF loans were even more infrequent. In comparison the most common rural social protection programmes (pension and disability) are given out monthly and are equal to a minimum wage per individual (R$ 10,560).

We also find that PRONAF is associated with with increased self-sufficiency in larger farms but associated with reduced self-sufficiency in larger households. Several studies have found PRONAF to increase food production (Eusebio et al., 2016; Garcias & Kassouf, 2016; Guanziroli & Basco, 2010), and a high proportion of PRONAF participants in our sample also expressed that PRONAF had resulted in an a more productive and more diversified farm. With more farm land available farmers are enabled to diversify production, and in particular it could allow for both crop production and animal husbandry, and a range of food types to be retained (in part) by the household for consumption. In fact, 76% of households with PRONAF were mixed farmers. With the increase of household members and the increased need for food it is likely that households rely more on purchased food than own produce. That, however, is assuming that the increase of household members also signify an increase in active household members and income (on-farm or off-farm) that enables increased food purchases.

Decisions around agro-chemical use for farmers in our study appears influenced by two contrasting motivations within the Zero Hunger programmes, i.e. to increase food production (by using more inputs) and to produce healthier food (by reducing inputs). We believe this is driving the lack of consistent patterns between participation in the Zero Hunger programmes for both inorganic fertilizer use and pesticide use. Divergent results of PAAs influence on agro-chemical input use are also found across other studies (Chmielewska et al., 2010; Doretto & Michellon, 2007; Mesquita & Bursztyn, 2017; Oliveira et al., 2017; Wittman & Blesh, 2017). Existing literature of PRONAF's influence on agro-chemical use show negligible effects (Damasceno et al., 2011; Godoi et al., 2016).

Lastly, we find beneficial relationships between both Bolsa Familia participation and PAA participation and natural vegetation when considering records of natural vegetation loss from the first year of participation. The beneficial relationship between Bolsa Familia, however, only occur for larger households. More research into the mechanisms behind this relationship is needed. The positive association (i.e. reduced loss of natural vegetation) with PAA participation, however, is particularly promising seeing that we also find participation positively associated with food access and food self-sufficiency. As such, this Zero Hunger sub-programme appears capable of delivering positive effects for food security without simultaneously driving adverse environmental effects in terms of loss of natural vegetation. We do note, however, an overall low occurrence of natural vegetation loss amongst study participants. They seemed to have a generally high awareness of legal environmental restrictions and environmental accountability, and due to environmental monitoring in these municipalities the fear of being fined amongst farmers appears to have kept many farmers from deforesting.

5. Conclusion

Social protection programmes are common strategies to deliver improvements in social conditions and may also have environmental effects. Brazil's flagship Zero Hunger programme has been hailed as a successful programme to reduce food insecurity, to the point where similar programmes are being adopted in other developing countries. However, a growing body of research reveals instances wherein which the programme has been less effective, even non-beneficial. Concurrently little is known about the environmental sustainability of the programme. Focusing on three municipalities in the state of Minas Gerais, we find evidence of positive associations between Zero Hunger and its three main sub-programmes Bolsa Familia, PRONAF and PAA and food security. We find evidence, however, that more capable farmers, e.g. farmers with more land and education are participating in PRONAF and PAA, and reveal a limited involvement from the very smallest farmers, suggesting these programmes are unable to reach those farmers arguably most in need.

For those that do participate, however, we find that PRONAF participation is associated with reduced household food insecurity, all programmes are associated with increased food access, and PRONAF and PAA are associated with increased food self-sufficiency. We find no consistent patterns of association between participation and agro-chemical use (inorganic fertilizer and pesticide) and conclude that Zero Hunger (and sub-programmes) are not influencing sustainability as measured with these metrics. We find no evidence that participation adversely affects natural vegetation loss and overall in the study we record few households with vegetation losses. Instead, both Bola Familia and PAA participation is associated with reduced natural vegetation losses which suggests these two programmes are able to simultaneously deliver on measures of food security and sustainability when measured in terms of natural vegetation loss.

The associations found between programme participation and our focus outcomes are, however, mediated by specific demographic and socio-economic characteristics, in particular head of household gender and age, household size and land area, and the simultaneous support from other social protection programmes, e.g. rural pensions. We also identify local agricultural extension offices are vital in the effectiveness of the PRONAF and PAA sub-programmes as they assist in the inscription process of these programmes, they encourage more environmentally friendly farm practices and they can help manage these programmes in ways which avoids specific demographic and socio-economic characteristics to reduce programme effectiveness.

6. References.

Agência IBASE. (2008). Repercussões do programa Bolsa Família na segurança alimentar e nutricional das Familias beneficiadas. Rio de Janeiro.

Ahmed, M. H., & Mesfin, H. M. (2017). The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: empirical evidence from eastern Ethiopia. *Agricultural and Food Economics*, *5*(6), 1–20. http://doi.org/10.1186/s40100-017-0075-z

Alkire, S., & Santos, M. E. (2014). Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index. *World Development*, *59*, 251–274. http://doi.org/10.1016/j.worlddev.2014.01.026

Assunção, J., Gandour, C., Rocha, R., & Rocha, R. (2013). *Does Credit Affect Deforestation? Evidence from a Rural Credit Policy in the Brazilian Amazon*. Retrieved from http://climatepolicyinitiative.org/wp-content/uploads/2013/01/Does-Credit-Affect-Deforestation-Evidence-from-a-Rural-Credit-Policy-in-the-Brazilian-Amazon-Technical-Paper-English.pdf

Atlas Brazil. (2013). The MHDI: Atlas of Human Development in Brazil. Retrieved November 3, 2015, from http://www.atlasbrasil.org.br/2013/en/o_atlas/idhm/

Babigumira, R., Angelsen, A., Buis, M., Bauch, S., Sunderland, T., & Wunder, S. (2014). Forest Clearing in Rural Livelihoods: Household-Level Global-Comparative Evidence. *World Development*, *64*(S1), S67–S79. http://doi.org/10.1016/j.worlddev.2014.03.002

Ballard, T. J., Kepple, A. W., & Cafiero, C. (2013). *The food insecurity experience scale: development of a global standard for monitoring hunger worldwide* (Technical Paper). Rome.

Barlow, J., Gardner, T. A., Araujo, I. S., Avila-Pires, T. C., Bonaldo, A. B., Costa, J. E., … Peres, C. A. (2007). Quantifying the biodiversity value of tropical primary, secondary, and plantation forests. *Proceedings of the National Academy of Sciences*, *104*(47), 18555–18560. http://doi.org/10.1073/pnas.0703333104

Barrientos, A. (2017). Design and rural context in antipoverty transfers: Implications for programme outcomes. *Global Food Security*, *12*(March 2016), 103–108. http://doi.org/10.1016/j.gfs.2016.09.002

Beuchle, R., Grecchi, R. C., Shimabukuro, Y. E., Seliger, R., Eva, H. D., Sano, E., & Achard, F. (2015). Land cover changes in the Brazilian Cerrado and Caatinga biomes from 1990 to 2010 based on a systematic remote sensing sampling approach. *Applied Geography*, *58*, 116–127. http://doi.org/10.1016/j.apgeog.2015.01.017

Blesh, J., Hoey, L., Jones, A. D., Friedmann, H., & Perfecto, I. (2019). Development pathways toward ‘‘ zero hunger ”. *World Development*, *118*, 1–14. http://doi.org/10.1016/j.worlddev.2019.02.004

Bogale, A., & Shimelis, A. (2009). Household level determinants of food insecurity in rural areas of Dire Dawa, Eastern Ethiopia. *African Journal of Food, Agriculture, Nutrition and Development*, *9*(9), 1914–1926.

Burgess, R., & Pande, R. (2005). Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review*, *95*(3), 780–795. http://doi.org/10.1257/0002828054201242

Byerlee, D., Stevenson, J., & Villoria, N. (2014). Does intensification slow crop land expansion or encourage deforestation? *Global Food Security*, *3*(2), 92–98. http://doi.org/10.1016/j.gfs.2014.04.001

Calaboni, A., Tambosi, L. R., Igari, A. T., Farinaci, J. S., Metzger, J. P., & Uriarte, M. (2018). The forest transition in São Paulo, Brazil : historical patterns and potential drivers. *Ecology and Society*, *23*(4). http://doi.org/10.5751/ES-10270-230407

Castaneda, R. (2012). *Zero Hunger: The Brazilian experience*. Rome. Retrieved from http://www.un.org/en/zerohunger/challenge.shtml

Chappell, M. J. (2018). *Beginning to end hunger : food and the environment in Belo Horizonte, Brazil, and beyond*. Oakland: University of California Press.

Chmielewska, D., & Souza, D. (2011). The food security policy context in Brazil. Brasilia.

Chmielewska, D., Souza, D., & Lourete, A. A. (2010). *O programa de aquisição de Alimentos da Agricultura Familiar (PAA) e as práticas dos agricultores participantes orientada ao mercado: Estudo de caso no estado de Sergipe*. Brasilia.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.

Cunha, W. A. da, Freitas, A. F. de, & Salgado, R. J. dos S. F. (2017). Efeitos dos Programas Governamentais de Aquisição de Alimentos para a Agricultura Familiar em Espera Feliz, MG. *Revista de Economia e Sociologia Rural*, *55*(3), 427–444.

Damasceno, N. P., Khan, A. S., & Lima, P. V. P. S. (2011). O impacto do Pronaf sobre a sustentabilidade da agricultura familiar, geração de emprego e renda no Estado do Ceará. *Revista de Economia e Sociologia Rural*, *49*(1), 129–156. http://doi.org/10.1590/S0103-20032011000100006

de Mattos, E. J., & Bagolin, I. P. (2017). Reducing Poverty and Food Insecurity in Rural Brazil: the Impact of the Zero Hunger Program. *EuroChoices*, *16*(1), 43–49. http://doi.org/10.1111/1746-692X.12150

Devereux, S. (2016). Social protection for enhanced food security in sub-Saharan Africa. *Food Policy*, *60*, 52–62. http://doi.org/10.1016/j.foodpol.2015.03.009

Devereux, S., & Sabates-Wheeler, R. (2004). *Transformative social protection*. *IDS Working Paper*.

Dixon, J., Gulliver, A., & Gibbon, D. (2001). Summary: Farming Systems and Poverty: Improving farmers' livelihodds in a changing world. In M. Hall (Ed.), *Farming Systems and Poverty: Improving farmers' livelihodds in a changing world* (pp. 1–41). Rome and Washington.

Doretto, M., & Michellon, E. (2007). Avaliação dos Impactos Econômicos, Sociais e Culturais do

Programa de Aquisição de Alimentos no Paraná, (43), 107–138. Retrieved from http://www.iapar.pr.gov.br/arquivos/File/zip_pdf/aval_impact_econo.pdf

Edwards, D. P., Massam, M. R., Haugaasen, T., & Gilroy, J. J. (2017). Tropical secondary forest regeneration conserves high levels of avian phylogenetic diversity. *Biological Conservation*, *209*, 432–439. http://doi.org/10.1016/j.biocon.2017.03.006

EMBRAPA. (2018). Perguntas e Respostas - Eucalipto. Retrieved September 27, 2018, from https://www.embrapa.br/florestas/transferencia-de-tecnologia/eucalipto/perguntas-e-respostas

Ericksen, P. J. (2008). Conceptualizing food systems for global environmental change research. *Global Environmental Change*, *18*, 234–245. http://doi.org/10.1016/j.gloenvcha.2007.09.002

Eusebio, G. dos S., Maia, A. G., & Silveira, R. L. F. da. (2016). Impact of microcredit on small-farm agricultural production: evidence from Brazil. In *Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, MA, July 31-August 02*.

FAO. (2014). *The state of food insecurity in the world*. Rome. Retrieved from http://www.sidalc.net/cgi-bin/wxis.exe/?IsisScript=LVV.xis&method=post&formato=2&cantidad=1&expresion=mfn=002054

Feijó, R. L. C. (2013). *A maioridade do PRONAF: uma avaliação crítica do programa de apoio à agricultura familiar em seus 18 anos de vida. In: Texto para Discussão*. *FEA- RP, série Economia*. Ribeirão Preto.

Felker-Kantor, E., & Wood, C. H. (2012). Female-headed households and food insecurity in Brazil. *Food Security*, *4*(4), 607–617. http://doi.org/10.1007/s12571-012-0215-y

Galhena, D., Freed, R., & Maredia, K. M. (2013). Home gardens: a promising approach to enhance household food security and wellbeing. *Agriculture & Food Security*, *2*(1), 8. http://doi.org/10.1186/2048-7010-2-8

Garcias, M. de O., & Kassouf, A. L. (2016). Assessment of rural credit impact on land and labor productivity for Brazilian family farmers. *Nova Economia*, *26*(3), 721–746. http://doi.org/10.1590/0103-6351/2761

Godoi, T. G., Búrigo, F. L., & Cazella, A. A. (2016). A sustentabilidade dos financiamentos do PRONAF para a agricultura familiar. *Desenvolvimento e Meio Ambiente*, *38*, 637–661. http://doi.org/10.5380/dma.v38i0.42657

Guanziroli, C. E., & Basco, C. A. (2010). Construction of agrarian policies in Brazil: the case of the National Program to Strengthen Family Farming (PRONAF). *Econpapers*, 44–63.

Helfand, S. M., Moreira, A. R. B., & Jr., E. W. B. (2015). *Agricultural Productivity and Family Farms in Brazil : Creating Opportunities and Closing Gaps*.

Holmes, R., Hagen-Zanker, J., & Vandemoortele, M. (2011). Social protection in Brazil: Impacts on poverty, inequality and growth. *Development Progress Working Paper*. Retrieved from http://www.developmentprogress.org/sites/developmentprogress.org/files/resource_report/brazil_report_-_master_0_0.pdf

Hunke, P., Mueller, E. N., Schröder, B., & Zeilhofer, P. (2015). The Brazilian Cerrado : assessment of water and soil degradation in catchments under intensive agricultural use. *Ecohydrology*, *8*, 1154–1180. http://doi.org/10.1002/eco.1573

IFAD. (2010). *Rural poverty report 2011: New realities , new challenges: new opportunities for tomorrow ' s generation*. Rome: IFAD.

Jayne, T. S., Chamberlin, J., & Muyanga, M. (2014). Emerging Land Issues in African Agriculture : Poverty Reduction Strategies. *Stanford University's Global Food Policy and Food Security Symposium Series*.

Joly, C. ., Metzger, J. P., & Tabarelli, M. (2014). Experiences from the Brazilian Atlantic Forest : ecological findings and conservation initiatives. *New Phytologist*, *204*(3), 459–473.

Kibue, G. W., Liu, X., Zheng, J., zhang, X., Pan, G., Li, L., & Han, X. (2016). Farmers' Perceptions of Climate Variability and Factors Influencing Adaptation: Evidence from Anhui and Jiangsu, China. *Environmental Management*, *57*(5), 976–986. http://doi.org/10.1007/s00267-016-0661-y

Krishna Bahadur, K., Pant, L. P., Fraser, E. D. G., Shrestha, P. K., Shrestha, D., & Lama, A. (2016). Assessing links between crop diversity and food self-sufficiency in three agroecological regions of Nepal. *Regional Environmental Change*, *16*(5), 1239–1251. http://doi.org/10.1007/s10113-015-0851-9

Leão, M. M., & Maluf, R. S. (2013). *Effective public policies and active citizenship: Brazil´s experience of building a Food and Nutrition Security System*. Brasilia.

Liao, C., & Brown, D. G. (2018). Assessments of synergistic outcomes from sustainable intensification of agriculture need to include smallholder livelihoods with food production and ecosystem services. *Current Opinion in Environmental Sustainability*, *32*(April), 53–59. http://doi.org/10.1016/j.cosust.2018.04.013

Lopes, M. I. M. S., Santos, A. R. Dos, Cmargo, C. Z. S., Bulbovas, P., Giampaoli, P., & Domingos, M. (2015). Soil chemical and physical status in semideciduous Atlantic Forest fragments affected by atmospheric deposition in central-eastern São Paulo State, Brazil. *IForest*, *8*, 798–808. http://doi.org/10.3832/ifor1258-007

Lowder, S. K., Skoet, J., & Raney, T. (2016). The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide. *World Development*, *87*, 16–29. http://doi.org/10.1016/j.worlddev.2015.10.041

Mango, N., Zamasiya, B., & Makate, C. (2014). Factors influencing household food security among smallholder farmers in the Mudzi district of Zimbabwe. *Development*, *31*(4), 625–640. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/0376835X.2014.911694

Mengistu, M. G., Simane, B., Eshete, G., & Workneh, T. S. (2016). Factors affecting households' decisions in biogas technology adoption, the case of Ofla and Mecha Districts, northern

Ethiopia. *Renewable Energy*. http://doi.org/10.1016/j.renene.2016.02.066

Mesquita, P. S., & Bursztyn, M. (2017). Food acquisition programs in the Brazilian semi-arid region: benefits to farmers and impacts of climate change. *Food Security*, *9*(5), 1041–1051. http://doi.org/10.1007/s12571-017-0711-1

Meyfroidt, P. (2018). Trade-offs between environment and livelihoods: Bridging the global land use and food security discussions. *Global Food Security*, *16*, 9–16. http://doi.org/10.1016/j.gfs.2017.08.001

Mohammed, D., Bukar, U., Umar, J., Abdulsalam, B., & Dahiru, B. (2016). Analysis of food security among smallholder farming households in arid areas of Borno state, Nigeria. *Continental Journal of Agricultural Economics, Wilolud Journals*, *8*(1), 1–8. http://doi.org/10.5707/cjae.201

Mojo, D., Fischer, C., & Degefa, T. (2015). Social and environmental impacts of agricultural cooperatives: Evidence from Ethiopia. *International Journal of Sustainable Development and World Ecology*, *22*(5), 388–400. http://doi.org/10.1080/13504509.2015.1052860

Myers, N., Mittermeier, R. A., Mittermeier, C. G., Fonseca, G. A. B., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, *403*, 853–858.

Na, M., Gross, A. L., & Jr, K. P. W. (2015). Validation of the food access survey tool to assess household food insecurity in rural Bangladesh. *BMC Public Health*, *15*, 1–10. http://doi.org/10.1186/s12889-015-2208-1

Nehring, R., & McKay, B. (2013). *Scaling up local development initiatives: Brazil's Food Acquisition Programme*.

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., … Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, *520*(7545), 45–50. http://doi.org/10.1038/nature14324

Nisbet, E. K., & Zelenski, J. M. (2013). The NR-6 : a new brief measure of nature relatedness. *Frontiers in Psychology*, *4*(813), 1–11. http://doi.org/10.3389/fpsyg.2013.00813

Oldekop, J. a., Chappell, M. J., Peixoto, F. E. B., Paglia, A. P., do Prado Rodrigues, M. S., & Evans, K. L. (2015). Linking Brazil's food security policies to agricultural change. *Food Security*. http://doi.org/10.1007/s12571-015-0475-4

Oliveira, L. G. de, Batalha, M. O., & Pettan, K. B. (2017). Comparative assessment of the food purchase program and the national school feeding program's impact in Ubá, Minas Gerais, Brazil. *Ciência Rural*, *47*(1), 1–6. http://doi.org/10.1590/0103-8478cr20160395

Onasanya, O. A., & Obayelu, O. A. (2016). Turkish Journal of Agriculture - Food Science and Technology Determinants of Food Security Status of Maize-Based Farming Households in Southern Guinea Savannah Area of Oyo State , Nigeria . *Turkish Journal of Agriculture - Food Science and Technology*, *4*(5), 411–417.

Osorio, R. G., Souza, P. H. G. F. de, Soares, S. S. D., & Oliveira, L. F. B. de. (2011). *Perfil da pobreza no Brasil e sua evolução no período 2004-2009.*

Paes-Sousa, Rômulo, Aline Ribeiro Dantas de Teixeira Soares, F. K. (2011). Brazil: Broadening Social Protection and Integrating Social Policies. In *Sharing Innovative Experiences, Volume 18: Successful Social Protection Floor Experiencies* (p. 19). ILO.

Paes-Sousa, R., Santos, L. M. P., & Miazaki, É. S. (2011). Effects of a conditional cash transfer programme on child nutrition in Brazil. *Bulletin of the World Health Organization*, *89*(7), 496–503. http://doi.org/10.2471/BLT.10.084202

Perfecto, I. Vandermeer, J. and Wright, A. (2009). *Nature's matrix: Linking agriculture, conservation and food sovereignty*. London: Earthscan. Retrieved from http://climateandcapitalism.com/2012/10/17/natures-matrix/

Perfecto, I., & Vandermeer, J. (2010). The agroecological matrix as alternative to the land-sparing/agriculture intensification model. *Proceedings of the National Academy of Sciences*, *107*(13), 5786–5791. http://doi.org/10.1073/pnas.0905455107

Piperata, B. A., McSweeney, K., & Murrieta, R. S. (2016). Conditional Cash Transfers, Food Security, and Health: Biocultural Insights for Poverty-Alleviation Policy from the Brazilian Amazon. *Current Anthropology*, *57*(6), 806–826. http://doi.org/10.1086/688912

Rammohan, A., & Pritchard, B. (2014). The role of landholding as a determinant of food and nutrition insecurity in rural Myanmar. *World Development*, *64*, 597–608. http://doi.org/10.1016/j.worlddev.2014.06.029

Rasella, D., Aquino, R., Santos, C. a T., Paes-Sousa, R., & Barreto, M. L. (2013). Effect of a conditional cash transfer programme on childhood mortality: a nationwide analysis of Brazilian municipalities. *Lancet*, *382*(9886), 57–64. http://doi.org/10.1016/S0140-6736(13)60715-1

Rocha, C., Burlandy, L., & Maluf, R. (2012). Small farms and sustainable rural development for food security : The Brazilian experience. *Development Southern Africa*, *29*(4).

Samberg, L. H., Gerber, J. S., Ramankutty, N., Herrero, M., & West, P. C. (2016). Subnational distribution of average farm size and smallholder contributions to global food production. *Environmental Research Letters*, *11*(12), 1–11. http://doi.org/10.1088/1748-9326/11/12/124010

Schutter, O. De. (2013). *Interim report of the Special Rapporteur on the right to food*.

Sidaner, E., Balaban, D., & Burlandy, L. (2013). The Brazilian school feeding programme: an example of an integrated programme in support of food and nutrition security. *Public Health Nutrition*, *16*(6), 989–94. http://doi.org/10.1017/S1368980012005101

Silva, J. G. da, Grossi, M. E. Del, & França, C. G. de. (2011). *The Fome Zero (Zero Hunger) Program: The brazilian experience*. (J. G. da Silva, M. E. Del Grossi, & C. G. de França, Eds.). Brasilia.

Soares, F. V., Ribas, R. P., & Osorio, R. G. (2010). Evaluating the Impact of Brazil's Bolsa Familia: Cash transfer programs in comparative perspective, *45*(2), 173–190.

SOS Mata Atlântica. (2017). Desmatamento da Mata Atlântica cresce quase 60% em um ano » SOS Mata Atlântica. Retrieved September 20, 2018, from https://www.sosma.org.br/106279/desmatamento-da-mata-atlantica-cresce-quase-60-em-um-ano/

Stuart, E. a. (2010). Matching Methods for Causal Inference: A Review and a Look Forward, *25*(1), 1–21. http://doi.org/10.1214/09-STS313

Stuart, E. A., & Rubin, D. B. (2007). Best practices in quasi-experimental designs: Matching methods for causal inference (pp. 155–176).

Thorkildsen, K. (2014). Social-Ecological Changes in a Quilombola Community in the Atlantic Forest of Southeastern Brazil. *Human Ecology*. http://doi.org/10.1007/s10745-014-9691-3

Tscharntke, T., Clough, Y., Wanger, T. C., Jackson, L., Motzke, I., Perfecto, I., … Whitbread, A. (2012). Global food security, biodiversity conservation and the future of agricultural intensification. *Biological Conservation*, *151*(1), 53–59. http://doi.org/10.1016/j.biocon.2012.01.068

Tubiello, F. N., Salvatore, M., Ferrara, A. F., House, J., Federici, S., Rossi, S., … Smith, P. (2015). The Contribution of Agriculture, Forestry and other Land Use activities to Global Warming, 1990-2012. *Global Change Biology*, *21*(7), 2655–2660. http://doi.org/10.1111/gcb.12865

UNCTAD. (2015). Commodities and Development Report 2015: Smallholder Farmers and Sustainable Commodity Development. *United Nations Conference on Trade and Development*, 1–20. http://doi.org/UNCTAD/SUC/2014/5

UNDP-IPC. (2013). *Structured Demand and Smallholder Farmers in Brazil : the Case of PAA and PNAE*. Brasilia.

Verhofstadt, E., & Maertens, M. (2015). Can agricultural cooperatives reduce poverty? Heterogeneous impact of cooperative membership on farmers' welfare in Rwanda. *Applied Economic Perspectives and Policy*, *37*(1), 86–106. http://doi.org/10.1093/aepp/ppu021

Vyas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: How to use principal components analysis. *Health Policy and Planning*, *21*(6), 459–468. http://doi.org/10.1093/heapol/czl029

Wittman, H., & Blesh, J. (2017). Food Sovereignty and Fome Zero: Connecting Public Food Procurement Programmes to Sustainable Rural Development in Brazil. *Journal of Agrarian Change*, *17*(1), 81–105. http://doi.org/10.1111/joac.12131

World Bank. (2008). *World Development Report 2008: Agriculture for Development*. Washington DC, USA.

WWF-Brazil. (2016). *Brazil's New Forest Code: A guide for decision-makers in supply chains and governments*. http://doi.org/http://assets.wwf.org.uk/downloads/wwf_brazils_new_forest_code_guide_1.pdf

Yila, O. M., & Thapa, G. B. (2011). Adoption of agricultural land management technologies by smallholder farmers in the Jos Plateau Nigeria. *International Journal of Agricultural Sustainability*, *6*(4), 277–288.

Zago, N. (2016). Rural-urban migration , youth, and higher education. *Revista Brasileira de Educação*, *21*(64), 61–77.

7. Supplementary material

Table S1: Variables considered and used for creation on poverty index using Principal Component Analysis (PCA), based on theories and methodological consideration for socio-economic indices (Alkire & Santos, 2014; Vyas & Kumaranayake, 2006). In particular, only variables with noticeable variation were considered. Continuous variables were fairly normally distributed, the only exception being household land owned. The final variables used in index based on best internal consistency (Cronbachs' alpha, of 0.6 (0.7 upper limit)

Variable description (all variables considered)	**Scale**	**Used in index**
Health		
Head Household illness	Days without work due to illness	
Education		
Head Household education	Years of study	✓
Living standard		
House density	Eligible rooms to sleep per capita	
Telephone/Mobile	Number owned	✓
Car	Number owned	✓
Electrical Fan	Number owned	✓
Water use_cistern	1 = Yes, 0 = No	
Water use_publicnetwork	1 = Yes, 0 = No	✓
Water use_spring	1 = Yes, 0 = No	
Water use_well	1 = Yes, 0 = No	
Cooking_gas	1 = Yes, 0 = No	✓
Cooking_firewood/charcoal	1 = Yes, 0 = No	
Land owned	Hectare	✓
Demographic conditions		
Household size	Number household members	
Head Household gender	1 = Male, 0 = Female	
Head Household age	Years	
Head Household ethnicity_African	1 = African, 0 = Other	
Head Household ethnicity_Mixed	1 = Mixed, 0 = Other	
Head Household ethnicity_European	1 = European, 0 = Other	

Table S2. Descriptive statistics for all model variables, based on a household survey carried out between October 2016 and January 2017. Values are based on model sample sizes ranging 187 – 190 households, (besides for the truncated R$/ha fertilizer and pesticide models which have a sample size of 90 and 130, respectively). Mean and standard deviation is shows for continuous variables, frequency (%) of households in each category for categorical variables

Variable	Description	Mean (SD) / % frequency
Dependent variables		
FIES	Food insecurity scale (range 0-11) of self-expressed food insecurity in the last twelve months prior to interview, 0 = no food insecurity	1.01 (2.17)
Food access	Food access scale (range -6 to 6), capturing change in access of food (in terms of quality, quantity and diversity) since start of managing the farm. Negative values represent decreases in access, positive represent increases	2.06 (2.81)
Food Self. (%)	Measure of food self-sufficiency, i.e. proportion of household food consumption produced on the farm	33.64 (19.76)
Fertilizer (1/0)	Use of inorganic fertilizer in the last twelve months (0 = yes/1 = no)	0=52%, 1=48%
Pesticide (1/0)	Use of chemical pesticide in the last twelve months (0 = yes/1 = no)	0=30%, 1=70%
Fertilizer (R$/ha)	Cost of inorganic fertilizer in R$ per hectare farm land in the last twelve months	750 (2008)
Pesticide (R$/ha)	Cost of chemical pesticides in R$ per hectare farm land in the last twelve months	168 (540)
Natural Veg. loss (N/L/H)	Natural vegetation loss on the farm in hectare from 2003 to currently, on ordinal scale, i.e. None (0 ha), Little (>0 to 1 ha), and High (>1 ha)	N=85%, L=7%, H=8%
Programme targeted Natural Veg. loss (N/L/H)	Natural vegetation loss on the farm in hectare from first year of programme participation to currently, creating separate variables for ZH overall- Bolsa Familia-, PRONAF- and PAA, for non-participants capturing loss between 2003 and 2016 on ordinal scale, i.e. None (0 ha), Little (>0 to 1 ha), and High (>1 ha)	N=88-90%, L=5-6%, H=5-6%
Treatment variables		
ZH current (R$1000)	R$ received from three main Zero Hunger (ZH) programmes (Bolsa Familia, PRONAF and PAA) in the past twelve months	4.76 (7.69)
ZH total (yrs)	Sum of programme years, i.e. count of years participated in Bolsa Familia, PRONAF and PAA between 2003 and currently	8.27 (5.97)
PRONAF current (R$1000)	R$ received from PRONAF in the last twelve months	0.65 (2.42)
PRONAF total (R$1000)	R$ received from PRONAF between 2003 and currently	19.98 (37.06)
PAA current (R$1000)	R$ received from PAA in the last twelve months	3.24 (7.17)
PAA total (yrs)	Count of years participated in PAA between 2003 and currently	2.92 (3.54)
BF current (R$1000)	R$ received from Bolsa Familia (BF) in the last twelve months	0.87 (2.13)
BF total (yrs)	Count of years participated in Bolsa Familia (BF) between 2003 and currently	3.94 (4.56)
Confounding variables		
HH age (yrs)	Head of household age	52.86 (13.54)

HH education (yrs)	Head of household years of study	5.07 (3.71)
House size	Household size (household family members that share common resources)	3.52 (1.46)
Poverty index	Poverty index created through PCA (see Table S1)	0 (1.38)
Land area (ha)	Total land area (ha) owned and managed by household	19.41 (39.66)
Property (yrs)	Total years managing the farm	23.61 (15.01)
FarmExp (R$1000)	Total farm expenses in R$ in the last twelve months	14.11 (33.44)
AgCredit (R$1000)	Total non-PRONAF agricultural credit received between 2003 and currently	1.54 (8.02)
SocSec (R$1000)	Total R$ received from non-ZH social protection programmes in the last twelve months	9.49 (15.35)
HH gender (F/M)	Gender head of household (Female and Male)	F=11%, M=89%
HH ethnicity (A/E/M)	Ethnicity head of household (African descendant, European descendant and Mixed-race)	A=17%, E=25%, M = 58%
FarmType (C/M/P)	Dominant farm type (Crop dominant = >95% arable, Pasture dominant = >95% pasture, Mixed farm = all other)	C=36%, M=44%, P=20%
AgCoop. (y/n)	Current participation in an agricultural cooperative (Yes, No)	Y=60%, N=40%
AgTraining (y/n)	Household members agricultural training (Yes, No)	Y=43%, N=57%
Municipality (MC, OV, PN)	Household municipal location (Montes Claros, Ouro Verde and Ponte Nova)	MC=35%, OV=33%, PN=32%

Table S3. Average demographic and socioeconomic characteristics for sampled households, and mean differences in participation within Zero Hunger overall-, and the Bolsa Familia, PRONAF and PAA sub-programmes. Participation is defined as households currently participating (within last 12 months). For the categorical variables instead of mean values and differences we report the proportion of respondents that participate for each level of the categorical variables. Significance levels for continuous variables are based on Two-Sample T-tests while for categorical variables on Chi-squared tests: # $P < 0.1$; * $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$. Reals (R$) is the Brazilian currency; £1 is approximately 5 R$

		Mean differences Participant vs. Non-Participant			
Variables	***Mean (SD) all respondents***	*Zero Hunger*	*Bolsa Familia*	*PRONAF*	*PAA*
Head of household (HH) gender (male/female)		Male 70% participate Female 70% participate	Male 37% participate Female 35% participate	Male 17% participate Female 10% participate	Male 46% participate Female 45% participate
HH age (years)	53 (14)	-11.69***	-11.73***	-5.19*	-4.13*
HH education level (school years)	5.07 (3.72)	#1.02	-0.55	#1.1	1.49**
HH ethnicity (African descendant., European, Mixed race)		African 64% participate European 70% participate Mixed 72% participate	# African 36% participate European 23% participate Mixed 43% participate	African 9% participate European 13% participate Mixed 19% participate	* African 39% participate European 62% participate Mixed 40% participate
Household size (members)	3.51 (1.47)	0.15	0.77***	0.02	#-0.37
Farm type (Crop, Pasture and Mixed)		Crop 71% participate Pasture 68% participate Mixed 71% participate	Crop 40% participate Pasture 37% participate Mixed 35% participate	Crop 19% participate Pasture 18% participate Mixed 12% participate	# Crop 46% participate Pasture 45% participate Mixed 46% participate
Land size (ha)	19 (40)	0.4	-11.35*	-3.99	7.29**
Property years	24 (15)	-3.25	-7.96***	-2.33	1.99
Agricultural credit (total R$)	1,548 (8037)	736	229	-1,523	2,000*
Other social protection (annual R$)	9,536 (15,379)	-9,715***	-11,190***	-4,076	-3,519
Municipality (Montes Claros, Ouro Verde and Ponte Nova)		** MC 71% participate OV 84% participate PN 55% participate	*** MC 33% participate OV 62% participate PN 15% participate	* MC 12% participate OV 27% participate PN 8% participate	MC 44% participate OV 49% participate PN 43% participate
Sample size (participant / non-participant)		133 / 56	70 / 119	30 / 159	86 / 103

Note* for Land size, Agricultural credit and Other social protection the variables are log10 transformed prior to statistical tests but mean differences reported are raw (untransformed) values

Table S4. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current $\log_{10}$(R$), total $\log_{10}$(R$) and total (years) participation, on household Food insecurity (food insecurity scale range 0-11), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold.

	Zero Hunger				**Bolsa Familia**				**PRONAF**				**PAA**			
	Current (R$1000)		*Total (yrs)*		*Current (R$1000)*		*Total (yrs)*		*Current (R$1000)*		*Total (R$1000)*		*Current (R$1000)*		*Total (yrs)*	
	Model 1		***Model 2***		***Model 3***		***Model 4***		***Model 5***		***Model 6***		***Model 7***		***Model 8***	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	-0.34±1.79	0.85	-0.39±1.75	0.83	-0.61±1.77	0.73	-0.47±1.72	0.78	-0.22±1.91	0.91	-1.3±1.7	0.45	-0.47±1.60	0.77	-0.37±1.61	0.82
Prog.Part.	-0.10±0.25	0.70	-0.01±0.04	0.84	0.004±0.27	0.99	0.03±0.05	0.54	0.17±0.43	0.70	1.43±0.8	0.07	-0.19±0.38	0.61	-0.13±0.08	0.12
Prog.Part.:Hsize											**-0.54±0.23**	**0.02**				
Prev.Part.	-0.0006±0.04	0.99			0.03±0.05	0.60			-0.36±0.39	0.35			-0.11±0.10	0.28		
Oth.ZH.Curr.Part.					-0.26±0.30	0.40			-0.13±0.28	0.63			0.11±0.24	0.63		
Oth.ZH.Prev.Part.					-0.07±0.08	0.38			0.01±0.05	0.92			0.01±0.05	0.81		
Oth.ZH.Total.Part.							-0.09±0.06	0.18			0.01±0.04	0.73			0.02±0.04	0.62
HHgenderMale	0.57±0.84	0.50	0.58±0.82	0.48	0.41±0.83	0.62	0.42±0.81	0.61	0.54±0.89	0.54	0.54±0.75	0.47	0.38±0.76	0.62	0.35±0.76	0.65
HHage	-0.01±0.02	0.59	-0.01±0.02	0.66	-0.01±0.02	0.60	-0.01±0.02	0.67	-0.01±0.03	0.61	-0.01±0.02	0.72	-0.01±0.02	0.68	-0.01±0.02	0.57
HHeducation	-0.05±0.08	0.51	-0.06±0.08	0.47	-0.01±0.09	0.94	-0.01±0.09	0.91	-0.04±0.09	0.68	-0.04±0.08	0.65	-0.02±0.08	0.81	-0.02±0.08	0.78
HHethnicityMixed	0.54±0.61	0.37	0.52±0.59	0.38	0.63±0.60	0.29	0.59±0.58	0.31	0.55±0.66	0.41	0.38±0.56	0.50	0.69±0.55	0.21	0.71±0.55	0.20
HHethnicityWhite	1.06±0.71	0.13	1.01±0.67	0.13	1.26±0.71	0.08	1.16±0.68	0.09	1.17±0.76	0.13	1.04±0.63	0.10	1.23±0.65	0.06	1.22±0.64	0.06
Hsize	0.03±0.15	0.86	0.03±0.14	0.83	-0.01±0.15	0.93	-0.02±0.15	0.91	0.02±0.15	0.88	0.23±0.14	0.10	-0.02±0.14	0.88	-0.02±0.14	0.90
Poverty	0.45±0.24	0.07	0.44±0.24	0.06	0.48±0.24	0.05	0.47±0.24	0.05	0.49±0.26	0.07	0.45±0.21	0.03	0.46±0.22	0.04	0.46±0.22	0.04
log10Land(ha)	-0.09±0.37	0.82	-0.08±0.36	0.82	0.003±0.36	0.99	-0.01±0.35	0.97	-0.08±0.40	0.83	-0.16±0.34	0.63	0.02±0.33	0.96	0.01±0.33	0.97
Prop.Years	-0.01±0.02	0.41	-0.01±0.02	0.41	-0.01±0.02	0.51	-0.01±0.02	0.50	-0.01±0.02	0.43	-0.01±0.02	0.37	-0.01±0.01	0.50	-0.01±0.01	0.46
log10FarmExp(R$1000)	-0.10±0.24	0.66	-0.12±0.23	0.59	-0.04±0.25	0.86	-0.08±0.23	0.72	-0.05±0.27	0.84	0.05±0.22	0.83	-0.12±0.21	0.58	-0.12±0.21	0.59
log10AgCred(R$1000)	-0.68±0.85	0.43	-0.70±0.83	0.40	-0.62±0.84	0.46	-0.7±0.81	0.39	-0.7±0.92	0.45	-0.73±0.77	0.34	-0.54±0.78	0.49	-0.54±0.78	0.49
FarmMixed	-0.36±0.51	0.48	-0.35±0.50	0.49	-0.27±0.49	0.58	-0.27±0.48	0.58	-0.24±0.56	0.67	-0.15±0.47	0.76	-0.27±0.46	0.55	-0.28±0.46	0.54
FarmPastureDom.	-0.40±0.66	0.54	-0.39±0.64	0.55	-0.49±0.66	0.46	-0.5±0.65	0.44	-0.38±0.71	0.59	-0.17±0.60	0.77	-0.44±0.61	0.47	-0.47±0.60	0.44
AgCooperativeYes	0.54±0.41	0.19	0.52±0.39	0.19	0.48±0.41	0.24	0.45±0.39	0.25	0.56±0.44	0.21	0.53±0.37	0.15	0.42±0.37	0.26	0.43±0.37	0.24
AgTrainingYes	-0.01±0.45	0.98	-0.01±0.44	0.98	0.25±0.45	0.58	0.23±0.44	0.60	0.11±0.49	0.82	-0.21±0.43	0.62	0.28±0.42	0.51	0.26±0.42	0.54
log10Soc.Sec(R$1000)	-0.52±0.43	0.23	-0.54±0.42	0.20	-0.46±0.42	0.27	-0.47±0.41	0.25	-0.52±0.45	0.25	-0.61±0.39	0.12	-0.48±0.39	0.23	-0.46±0.39	0.24
Municip.OuroVerde	1.09±0.50	0.03	1.05±0.47	0.03	1.04±0.52	0.05	0.98±0.46	0.03	1.11±0.55	0.05	1.37±0.48	0.005	0.82±0.46	0.08	0.88±0.43	0.04
Municip.PonteNova	0.15±0.52	0.77	0.17±0.51	0.74	0.18±0.51	0.72	0.14±0.49	0.77	0.05±0.55	0.92	0.15±0.48	0.76	0.25±0.47	0.60	0.23±0.47	0.62
Observations	189	189	189	189	190	190	190	190	189	189	189	189	190	190	190	190

R2	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Table S5. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme total $\log_{10}$(R$) and total (years) participation on change in household Food access (food access scale range -6 to 6), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	Zero Hunger				**Bolsa Familia**		**PRONAF**		**PAA**			
	Total (yrs) *Model 1*		*Total (yrs)* *Model 2*		*Total (yrs)* *Model 3*		*Total (R$1000)* *Model 4*		*Total (yrs)* *Model 5*		*Total (yrs)* *Model 6*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	-0.39±2.04	0.85	1.15±1.92	0.55	1.04±1.92	0.59	2.04±1.88	0.28	3.85±1.92	0.05	2.68±1.86	0.15
Prog.Part.	**0.39±0.13**	**0.003**	**0.13±0.06**	**0.04**	**0.43±0.2**	**0.04**	0.40±0.37	0.28	**-0.56±0.24**	**0.02**	-0.03±0.09	0.75
Prog.Part.:HHgenderMale	**-0.38±0.13**	**0.004**			**-0.45±0.20**	**0.03**						
Prog.Part.:AgCooperativeYes			**-0.15±0.07**	**0.04**								
Prog.Part.:HHage									**0.01±0.004**	**0.005**		
Prog.Part.:Soc.Sec(R$1000)											**0.2±0.09**	**0.03**
Oth.ZH.Total.Part.					0.07±0.06	0.21	0.03±0.05	0.49	-0.002±0.05	0.97	0.004±0.05	0.94
HHgenderMale	2.95±1.13	0.01	0.34±0.70	0.63	1.47±0.85	0.09	0.38±0.71	0.59	0.42±0.70	0.55	0.44±0.70	0.53
HHage	-0.003±0.02	0.91	0.01±0.03	0.82	-0.004±0.02	0.88	-0.002±0.03	0.95	-0.03±0.03	0.26	-0.0001±0.02	1.00
HHeducation	-0.01±0.08	0.94	0.02±0.08	0.85	-0.02±0.08	0.81	-0.02±0.08	0.81	-0.02±0.08	0.78	-0.02±0.08	0.81
HHethnicityMixed	0.27±0.57	0.64	-0.05±0.59	0.93	0.26±0.58	0.65	0.16±0.59	0.79	0.05±0.57	0.93	0.18±0.58	0.76
HHethnicityWhite	-0.38±0.68	0.58	-0.54±0.69	0.44	-0.4±0.68	0.56	-0.39±0.69	0.57	-0.43±0.68	0.53	-0.48±0.69	0.48
Hsize	0.003±0.14	0.99	-0.02±0.14	0.88	0.03±0.15	0.84	-0.02±0.15	0.91	0.02±0.15	0.91	-0.03±0.15	0.86
Poverty	-0.49±0.20	0.01	-0.53±0.20	0.01	-0.48±0.20	0.02	-0.52±0.20	0.01	-0.48±0.20	0.02	-0.51±0.20	0.01
log10Land(ha)	-0.47±0.45	0.30	-0.62±0.46	0.18	-0.41±0.46	0.38	-0.63±0.47	0.18	-0.61±0.45	0.18	-0.62±0.46	0.18
Prop.Years	0.005±0.02	0.77	0.005±0.02	0.78	0.01±0.02	0.75	0.004±0.02	0.83	0.0005±0.02	0.97	0.004±0.02	0.81
log10FarmExp(R$1000)	0.39±0.30	0.19	0.35±0.30	0.25	0.31±0.30	0.30	0.29±0.32	0.36	0.41±0.29	0.16	0.41±0.30	0.17
log10AgCred(R$1000)	-0.24±0.72	0.74	-0.22±0.73	0.76	-0.28±0.72	0.70	-0.15±0.73	0.83	-0.13±0.73	0.85	-0.13±0.74	0.86
FarmMixed	-0.43±0.57	0.45	-0.18±0.58	0.75	-0.49±0.58	0.40	-0.41±0.58	0.48	-0.27±0.57	0.63	-0.32±0.57	0.58
FarmPastureDom.	-1.38±0.72	0.06	-1.12±0.73	0.13	-1.38±0.73	0.06	-1.22±0.73	0.10	-1.16±0.72	0.11	-1.31±0.72	0.07
AgCooperativeYes	0.13±0.46	0.77	1.30±0.72	0.07	0.15±0.46	0.75	0.16±0.47	0.73	0.15±0.45	0.75	0.09±0.46	0.84
AgTrainingYes	0.10±0.48	0.84	0.18±0.49	0.72	0.18±0.49	0.71	0.15±0.50	0.76	0.22±0.49	0.65	0.17±0.49	0.73
log10Soc.Sec(R$1000)	0.33±0.42	0.42	0.24±0.42	0.57	0.25±0.42	0.56	0.29±0.43	0.50	0.22±0.42	0.60	-0.3±0.49	0.54
Municip.OuroVerde	-0.69±0.57	0.23	-0.83±0.58	0.16	-0.73±0.57	0.21	-0.70±0.58	0.23	-0.62±0.57	0.28	-0.74±0.58	0.20
Municip.PonteNova	0.10±0.53	0.85	0.05±0.54	0.92	0.05±0.54	0.93	0.06±0.55	0.91	-0.25±0.54	0.64	-0.38±0.56	0.50
Observations	189		189		190		189		190		190	
R2	0.194		0.174		0.183		0.159		0.198		0.182	

Table S6. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current log_{10}(R$), total log_{10}(R$) and total (years) participation, on household Food Self-Sufficiency (proportion of household consumption produced on the farm), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	Zero Hunger				**Bolsa Familia**			
	Current (R$1000)		*Total (yrs)*		*Current (R$1000)*		*Total (yrs)*	
	Model 1		*Model 2*		*Model 3*		*Model 4*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	28.26±13.67	0.04	28.47±13.65	0.04	28.93±13.57	0.03	28.28±13.63	0.04
Prog.Part.	0.91±1.72	0.60	0.21±0.31	0.51	2.81±2.26	0.21	-0.03±0.43	0.94
Prev.Part.	0.12±0.36	0.75			-0.24±0.48	0.62		
Oth.ZH.Curr.Part.					-0.88±2.40	0.71		
Oth.ZH.Prev.Part.					0.65±0.51	0.21		
Oth.ZH.Total.Part.							0.54±0.43	0.21
HHgenderMale	1.08±5.17	0.83	0.86±5.14	0.87	1.83±5.19	0.72	1.06±5.14	0.84
HHage	-0.08±0.19	0.69	-0.10±0.18	0.57	-0.06±0.19	0.74	-0.09±0.18	0.61
HHeducation	0.80±0.57	0.16	0.81±0.57	0.16	0.83±0.59	0.16	0.71±0.58	0.22
HHethnicityMixed	-1.59±4.27	0.71	-1.42±4.24	0.74	-1.41±4.27	0.74	-1.49±4.23	0.73
HHethnicityWhite	-1.21±5.12	0.81	-0.74±4.99	0.88	-0.94±5.14	0.86	-1.02±4.99	0.84
Hsize	-0.32±1.06	0.76	-0.39±1.05	0.71	-0.26±1.13	0.82	-0.06±1.12	0.96
Poverty	2.25±1.47	0.13	2.19±1.46	0.14	2.19±1.47	0.14	2.27±1.47	0.12
log10Land(ha)	0.91±3.26	0.78	0.80±3.25	0.81	1.34±3.27	0.68	0.80±3.25	0.81
Prop.Years	0.23±0.13	0.07	0.24±0.13	0.06	0.24±0.13	0.07	0.22±0.13	0.09
log10FarmExp(R$1000)	1.75±2.23	0.43	1.97±2.18	0.37	1.81±2.24	0.42	1.78±2.20	0.42
log10AgCred(R$1000)	0.02±5.32	1.00	0.07±5.30	0.99	0.03±5.34	1.00	-0.31±5.32	0.95
FarmMixed	4.83±4.23	0.25	4.79±4.21	0.26	3.63±4.29	0.40	4.05±4.24	0.34
FarmPastureDom.	-1.16±5.34	0.83	-1.05±5.33	0.84	-1.34±5.33	0.80	-1.19±5.32	0.82
AgCooperativeYes	2.41±3.37	0.48	2.37±3.36	0.48	1.83±3.38	0.59	2.26±3.36	0.50
AgTrainingYes	-2.98±3.57	0.41	-3.01±3.57	0.40	-3.90±3.61	0.28	-4.21±3.60	0.24
log10Soc.Sec(R$1000)	-2.82±3.11	0.37	-2.57±3.08	0.41	-2.47±3.13	0.43	-2.83±3.11	0.36
Municip.OuroVerde	-6.45±4.31	0.14	-6.23±4.26	0.15	-7.54±4.52	0.10	-5.97±4.25	0.16
Municip.PonteNova	1.78±3.95	0.65	1.75±3.94	0.66	2.26±3.97	0.57	1.69±3.94	0.67
Observations	189		189		190		190	
R2	0.103		0.103		0.114		0.106	

Table S6 continued. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current log_{10}(R$), total log_{10}(R$) and total (years) participation on household Food Self-Sufficiency (proportion of household consumption produced on the farm), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	PRONAF						**PAA**			
	Current (R$1000)		*Total (R$1000)*		*Total (R$1000)*		*Current (R$1000)*		*Total (yrs)*	
	Model 5		*Model 6*		*Model 7*		*Model 8*		*Model 9*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	22.14±14.01	0.12	18.35±14.54	0.21	31.99±13.59	0.02	27.33±13.34	0.04	31.74±13.51	0.02
Prog.Part.	-9.31±6.60	0.16	9.09±6.09	0.14	-6.62±3.45	0.06	-6.83±3.66	0.06	-0.03±0.63	0.96
Prog.Part.:log10Land(ha)	**12.57±5.50**	**0.02**								
Prog.Part.:Hsize			**-3.20±1.61**	**0.05**						
Prog.Part.:log10Soc.Sec(R$1000)					**7.07±3.21**	**0.03**	**7.25±3.62**	**0.05**	**1.44±0.65**	**0.03**
Prev.Part.	-3.43±2.74	0.21					1.15±0.63	0.07		
Oth.ZH.Curr.Part.	1.15±1.75	0.51					2.72±1.86	0.15		
Oth.ZH.Prev.Part.	0.16±0.39	0.68					-0.40±0.42	0.35		
Oth.ZH.Total.Part.			0.36±0.34	0.30	0.38±0.34	0.27			-0.08±0.39	0.83
HHgenderMale	-0.30±5.13	0.95	1.39±5.10	0.79	0.50±5.09	0.92	2.32±5.09	0.65	1.7±5.09	0.74
HHage	-0.05±0.19	0.79	-0.07±0.18	0.69	-0.11±0.18	0.56	-0.02±0.19	0.90	-0.08±0.18	0.67
HHeducation	0.92±0.57	0.11	1.02±0.57	0.08	1.06±0.57	0.07	0.85±0.57	0.14	0.75±0.57	0.19
HHethnicityMixed	-1.69±4.22	0.69	-1.85±4.22	0.66	-2.08±4.22	0.62	-1.83±4.20	0.66	-1.81±4.17	0.66
HHethnicityWhite	-0.88±5.09	0.86	-1.80±4.99	0.72	-0.44±4.95	0.93	-0.61±5.10	0.91	-1.72±4.93	0.73
Hsize	-0.35±1.06	0.74	1.39±1.42	0.33	-0.51±1.05	0.63	-0.05±1.09	0.96	-0.25±1.10	0.82
Poverty	2.90±1.47	0.05	2.30±1.45	0.12	2.77±1.47	0.06	2.63±1.45	0.07	2.23±1.45	0.13
log10Land(ha)	11.07±5.42	0.04	1.07±3.25	0.74	0.81±3.25	0.80	1.31±3.21	0.68	0.20±3.22	0.95
Prop.Years	0.22±0.13	0.09	0.26±0.13	0.04	0.24±0.13	0.06	0.23±0.13	0.08	0.23±0.13	0.07
log10FarmExp(R$1000)	2.44±2.33	0.30	3.08±2.32	0.19	3.26±2.32	0.16	2.05±2.17	0.35	2.21±2.15	0.31
log10AgCred(R$1000)	0.42±5.27	0.94	0.98±5.30	0.85	0.46±5.26	0.93	-0.59±5.28	0.91	0.04±5.32	0.99
FarmMixed	5.10±4.26	0.23	5.06±4.22	0.23	5.17±4.20	0.22	3.46±4.22	0.41	4.67±4.19	0.27
FarmPastureDom.	-1.37±5.29	0.80	-1.07±5.28	0.84	-1.36±5.27	0.80	-1.91±5.24	0.72	-1.66±5.25	0.75
AgCooperativeYes	3.06±3.34	0.36	2.33±3.34	0.49	2.52±3.33	0.45	2.13±3.30	0.52	1.58±3.33	0.64
AgTrainingYes	-1.47±3.68	0.69	-4.13±3.64	0.26	-2.98±3.57	0.41	-2.89±3.61	0.42	-4.40±3.58	0.22
log10Soc.Sec(R$1000)	-2.75±3.07	0.37	-2.52±3.07	0.41	-7.39±3.83	0.06	-3.72±3.07	0.23	-6.94±3.55	0.05
Municip.OuroVerde	-8.15±4.39	0.07	-3.86±4.35	0.38	-6.37±4.23	0.13	-6.64±4.42	0.13	-6.16±4.23	0.15
Municip.PonteNova	-0.43±3.98	0.91	1.91±3.95	0.63	-0.13±3.98	0.97	0.10±3.96	0.98	-0.91±4.03	0.82
Observations	189		189		189		190		190	
R2	0.143		0.127		0.131		0.152		0.137	

Table S7. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current $\log_{10}$(R$), total $\log_{10}$(R$) and total (years) participation on the likelihood of household expenditure on Inorganic fertilizer (per hectare), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	Zero Hunger				**Bolsa Familia**											
	Current (R$1000)		*Total (yrs)*		*Current (R$1000)*		*Current (R$1000)*		*Current (R$1000)*		*Total (yrs)*		*Total (yrs)*		*Total (yrs)*	
	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*		*Model 7*		*Model 8*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	1.08±2.08	0.61	1.63±2.10	0.44	2.49±2.19	0.25	1.15±2.08	0.58	0.98±2.10	0.64	1.39±2.09	0.50	-1.17±2.30	0.61	0.68±2.07	0.74
Prog.Part.	**0.59±0.28**	**0.04**	-0.09±0.08	0.25	0.39±0.36	0.28	0.54±0.44	0.23	0.19±0.35	0.58	-0.13±0.10	0.21	**0.49±0.24**	**0.04**	0.08±0.07	0.23
Prog.Part.: AgTrainingYes	**-0.89±0.41**	**0.03**			**-1.57±0.52**	**0.002**										
Prog.Part.: log10Land(ha)			**0.14±0.07**	**0.04**							**0.18±0.09**	**0.04**				
Prog.Part.: AgCooperativeYes							**-0.97±0.48**	**0.04**								
Prog.Part.:HHage													**-0.01±0.005**	**0.046**		
Prog.Part.: log10Soc.Sec (R$1000)									**-1.40±0.65**	**0.03**					**-0.23±0.10**	**0.02**
Prev.Part.	0.04±0.05	0.50			0.07±0.08	0.34	0.03±0.07	0.72	0.02±0.07	0.74						
Oth.ZH.Curr.Part.					0.53±0.35	0.13	0.57±0.35	0.11	0.50±0.35	0.16						
Oth.ZH.Prev.Part.					-0.04±0.08	0.64	-0.07±0.08	0.42	-0.02±0.08	0.82						
Oth.ZH.Total.Part.											0.03±0.07	0.69	0.03±0.07	0.67	0.03±0.07	0.70
HHgenderMale	-1.00±0.79	0.20	-0.94±0.80	0.24	-0.84±0.82	0.30	-0.78±0.82	0.34	-1.15±0.91	0.21	-0.91±0.80	0.25	-0.95±0.78	0.22	-0.98±0.79	0.22
HHage	-0.03±0.03	0.28	-0.04±0.03	0.17	-0.04±0.03	0.14	-0.02±0.03	0.53	-0.03±0.03	0.29	-0.04±0.03	0.16	-0.01±0.03	0.85	-0.05±0.03	0.08
HHeducation	0.04±0.08	0.57	0.04±0.08	0.62	0.01±0.08	0.90	0.06±0.08	0.50	0.02±0.08	0.83	0.03±0.08	0.71	0.06±0.08	0.49	0.05±0.08	0.55
HHethnicityMixed	0.90±0.67	0.18	1.31±0.65	0.04	0.85±0.71	0.23	0.77±0.67	0.25	1.04±0.66	0.11	1.17±0.63	0.06	1.22±0.64	0.06	1.19±0.64	0.06
HHethnicityWhite	1.40±0.78	0.07	1.95±0.79	0.01	1.15±0.83	0.17	1.01±0.80	0.21	1.45±0.80	0.07	1.68±0.75	0.02	1.78±0.77	0.02	1.83±0.77	0.02
Hsize	-0.17±0.15	0.27	-0.18±0.15	0.23	-0.23±0.18	0.20	-0.14±0.17	0.39	-0.02±0.18	0.93	-0.14±0.16	0.40	-0.08±0.17	0.62	-0.07±0.17	0.67
Poverty	0.16±0.23	0.50	0.13±0.23	0.57	0.21±0.23	0.35	0.25±0.23	0.26	0.22±0.23	0.35	0.10±0.23	0.67	0.24±0.22	0.29	0.22±0.22	0.32
log10Land(ha)	0.51±0.52	0.33	-0.74±0.79	0.35	0.39±0.51	0.44	0.55±0.51	0.28	0.17±0.52	0.75	-0.41±0.68	0.55	0.41±0.50	0.42	0.27±0.51	0.59
Prop.Years	-0.02±0.02	0.29	-0.02±0.02	0.33	-0.02±0.02	0.26	-0.02±0.02	0.29	-0.02±0.02	0.34	-0.01±0.02	0.49	-0.01±0.02	0.43	-0.01±0.02	0.53
log10FarmExp (R$1000)	2.58±0.60	<0.01	2.97±0.63	<0.01	2.67±0.62	<0.01	2.55±0.59	<0.01	2.70±0.61	<0.01	2.77±0.60	<0.01	2.59±0.58	<0.01	2.85±0.62	<0.01
log10AgCred (R$1000)	-0.61±0.73	0.40	-0.80±0.71	0.26	-0.12±0.74	0.87	-0.57±0.72	0.43	-0.62±0.70	0.38	-0.61±0.69	0.38	-0.59±0.69	0.40	-0.57±0.69	0.41
FarmMixed	-0.59±0.64	0.36	-0.55±0.64	0.40	-0.59±0.67	0.38	-0.64±0.65	0.33	-0.26±0.65	0.69	-0.46±0.65	0.48	-0.54±0.63	0.39	-0.26±0.64	0.69
FarmPastureDom.	-1.89±0.85	0.03	-1.69±0.84	0.05	-2.15±0.90	0.02	-2.11±0.85	0.01	-1.57±0.83	0.06	-1.6±0.84	0.06	-1.72±0.82	0.04	-1.62±0.82	0.05
AgCooperativeYes	-0.13±0.51	0.80	-0.07±0.48	0.89	0.04±0.50	0.93	-0.84±0.64	0.19	-0.05±0.51	0.93	0.06±0.49	0.91	0.16±0.49	0.74	-0.13±0.49	0.79
AgTrainingYes	-0.16±0.50	0.75	-0.09±0.48	0.85	-1.51±0.71	0.03	0.09±0.49	0.85	0.09±0.50	0.85	-0.01±0.48	0.98	-0.03±0.49	0.95	0.09±0.49	0.86

log10Soc.Sec (R$1000)	0.43±0.45	0.34	0.35±0.43	0.41	0.50±0.47	0.28	0.12±0.46	0.80	-1.70±1.04	0.10	0.34±0.44	0.43	0.10±0.46	0.83	0.96±0.52	0.07
Municip.OuroVerde	-1.68±0.63	0.01	-1.60±0.64	0.01	-1.75±0.67	0.01	-1.66±0.67	0.01	-1.59±0.68	0.02	-1.53±0.63	0.01	-1.45±0.62	0.02	-1.66±0.64	0.01
Municip.PonteNova	0.76±0.57	0.18	0.82±0.57	0.15	0.38±0.57	0.51	0.59±0.57	0.31	0.72±0.58	0.22	0.79±0.57	0.17	0.74±0.57	0.19	0.73±0.57	0.20
Observations	186		186		187		187		187		187		187		187	
McFadden R^2	0.422		0.416		0.44		0.416		0.426		0.41		0.408		0.413	

Table S7 continued. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current $\log_{10}$(R$), total $\log_{10}$(R$) and total (years) participation on the likelihood of household expenditure on Inorganic fertilizer (per hectare), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	PRONAF						**PAA**			
	Current (R$1000)		*Total (R$1000)*		*Total (R$1000)*		*Current (R$1000)*		*Total (yrs)*	
	Model 9		*Model 10*		*Model 11*		*Model 12*		*Model 13*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	1.50±2.13	0.48	2.72±2.21	0.22	1.25±2.08	0.55	1.09±2.06	0.60	1.05±2.02	0.60
Prog.Part.	0.68±0.53	0.20	-2.55±1.39	0.07	-0.52±0.52	0.32	-0.87±0.68	0.21	0.02±0.08	0.80
Prog.Part.:HHage			**0.05±0.02**	**0.04**						
Prog.Part.: log10Soc.Sec(R$1000)					**1.08±0.51**	**0.03**				
Prog.Part.: AgCooperativeYes							**1.76±0.78**	**0.02**		
Prev.Part.	-0.02±0.39	0.97					-0.03±0.09	0.73		
Oth.ZH.Curr.Part.	0.19±0.24	0.43					-0.07±0.27	0.80		
Oth.ZH.Prev.Part.	0.01±0.06	0.86					0.05±0.06	0.45		
Oth.ZH.Total.Part.			0.04±0.05	0.39	0.04±0.05	0.41			0.03±0.06	0.56
HHgenderMale	-0.97±0.80	0.23	-1.05±0.80	0.19	-1.26±0.83	0.13	-1.03±0.81	0.20	-1.01±0.78	0.19
HHage	-0.03±0.03	0.24	-0.07±0.03	0.02	-0.04±0.03	0.19	-0.04±0.03	0.15	-0.04±0.03	0.14
HHeducation	0.03±0.08	0.66	0.07±0.08	0.37	0.09±0.08	0.26	0.04±0.08	0.65	0.05±0.08	0.56
HHethnicityMixed	0.96±0.64	0.14	1.04±0.67	0.12	1.03±0.66	0.12	1.22±0.65	0.06	1.08±0.64	0.09
HHethnicityWhite	1.42±0.77	0.07	1.59±0.78	0.04	1.64±0.77	0.03	1.50±0.81	0.06	1.51±0.74	0.04
Hsize	-0.14±0.15	0.37	-0.16±0.15	0.29	-0.15±0.15	0.31	-0.15±0.16	0.36	-0.16±0.16	0.30
Poverty	0.23±0.23	0.32	0.28±0.23	0.24	0.31±0.23	0.17	0.16±0.24	0.50	0.21±0.22	0.34
log10Land(ha)	0.51±0.52	0.33	0.51±0.51	0.32	0.42±0.51	0.41	0.59±0.51	0.25	0.47±0.50	0.35
Prop.Years	-0.02±0.02	0.37	-0.02±0.02	0.42	-0.01±0.02	0.45	-0.01±0.02	0.50	-0.01±0.02	0.50
log10FarmExp(R$1000)	2.53±0.60	<0.001	2.73±0.60	<0.001	2.75±0.60	<0.001	2.64±0.59	<0.001	2.58±0.56	<0.001
log10AgCred(R$1000)	-0.36±0.69	0.60	-0.44±0.71	0.54	-0.31±0.70	0.66	-0.48±0.71	0.50	-0.49±0.70	0.48
FarmMixed	-0.52±0.64	0.42	-0.69±0.63	0.27	-0.61±0.64	0.34	-0.72±0.66	0.28	-0.53±0.62	0.39
FarmPastureDom.	-1.77±0.83	0.03	-1.88±0.83	0.02	-2.06±0.86	0.02	-2.13±0.88	0.02	-1.78±0.82	0.03

AgCooperativeYes	-0.03±0.49	0.95	-0.01±0.49	0.98	-0.07±0.50	0.88	-0.08±0.49	0.86	-0.02±0.48	0.96
AgTrainingYes	0.04±0.52	0.94	-0.17±0.51	0.74	-0.13±0.51	0.79	0.19±0.51	0.71	0.04±0.48	0.94
log10Soc.Sec(R$1000)	0.29±0.44	0.50	0.43±0.44	0.33	-0.41±0.56	0.46	0.42±0.43	0.33	0.35±0.42	0.41
Municip.OuroVerde	-1.76±0.65	0.01	-1.55±0.61	0.01	-1.63±0.62	0.01	-1.65±0.65	0.01	-1.6±0.62	0.01
Municip.PonteNova	0.74±0.57	0.19	0.61±0.58	0.29	0.55±0.58	0.34	0.51±0.58	0.38	0.66±0.56	0.24
Observations	186		186		186		187		187	
McFadden R^2	0.407		0.417		0.418		0.414		0.392	

Table S8. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current log_{10}(R$), total log_{10}(R$) and total (years) participation on the likelihood of household expenditure on Chemical pesticide (per hectare), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	Zero Hunger								**Bolsa Familia**					
	Current (R$1000)		*Current (R$1000)*		*Total (yrs)*		*Total (yrs)*		*Current (R$1000)*		*Total (yrs)*		*Total (yrs)*	
	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*		*Model 7*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	-0.47±1.67	0.78	-1.08±1.64	0.51	-2.73±1.80	0.13	-2.53±1.74	0.15	-0.67±1.70	0.69	-2.69±1.77	0.13	-1.66±1.66	0.32
Prog.Part.	**-0.60±0.31**	**0.048**	-0.59±0.33	0.07	0.20±0.11	0.08	**0.18±0.09**	**0.04**	-0.07±0.37	0.85	**0.55±0.25**	**0.03**	0.12±0.07	0.10
Prog.Part.:AgCooperativeYes	**0.91±0.36**	**0.01**												
Prog.Part.:log10Land(ha)			**0.58±0.26**	**0.03**										
Prog.Part.:HHgenderMale					**-0.23±0.11**	**0.04**					**-0.54±0.25**	**0.03**		
Prog.Part.:Hsize							**-0.06±0.02**	**0.02**						
Prog.Part.:FarmMixed									**-0.99±0.44**	**0.03**			**-0.21±0.09**	**0.02**
Prog.Part.:FarmPastureDom.									-0.30±0.50	0.55			-0.08±0.10	0.44
Prev.Part.	-0.01±0.04	0.79	-0.02±0.04	0.67					0.07±0.06	0.23				
Oth.ZH.Curr.Part.									0.17±0.30	0.56				
Oth.ZH.Prev.Part.									-0.12±0.06	0.06				
Oth.ZH.Total.Part.											-0.08±0.05	0.13	-0.08±0.05	0.14
HHgenderMale	0.61±0.58	0.29	0.62±0.58	0.29	2.33±0.98	0.02	0.73±0.58	0.21	0.41±0.60	0.49	1.84±0.74	0.01	0.70±0.58	0.23
HHage	-0.01±0.02	0.81	0.01±0.02	0.67	0.01±0.02	0.58	0.01±0.02	0.62	0.004±0.02	0.86	0.01±0.02	0.64	0.01±0.02	0.67
HHeducation	-0.01±0.07	0.88	0.01±0.07	0.89	0.02±0.07	0.75	0.003±0.07	0.97	0.02±0.07	0.81	0.06±0.07	0.42	0.04±0.07	0.55
HHethnicityMixed	0.14±0.51	0.78	0.13±0.51	0.80	0.07±0.51	0.89	-0.07±0.51	0.90	-0.10±0.51	0.85	0.07±0.51	0.89	0.09±0.51	0.86
HHethnicityWhite	0.29±0.63	0.65	0.19±0.62	0.76	0.10±0.61	0.86	0.07±0.61	0.90	-0.001±0.64	1.00	0.17±0.62	0.78	0.16±0.60	0.79
Hsize	0.01±0.13	0.94	-0.01±0.13	0.92	0.02±0.13	0.89	0.45±0.23	0.05	-0.01±0.15	0.92	-0.04±0.14	0.79	-0.05±0.14	0.70
Poverty	-0.02±0.18	0.90	0.09±0.19	0.62	0.05±0.17	0.78	0.08±0.18	0.68	0.10±0.18	0.60	0.06±0.18	0.74	0.05±0.18	0.79
log10Land(ha)	-0.01±0.39	0.98	-0.09±0.40	0.82	0.05±0.38	0.90	0.003±0.38	0.99	0.03±0.40	0.94	0.26±0.41	0.53	0.04±0.40	0.93
Prop.Years	-0.003±0.02	0.86	-0.01±0.02	0.48	-0.01±0.02	0.60	-0.01±0.02	0.36	-0.01±0.02	0.72	0.00002±0.02	1.00	-0.01±0.02	0.72
log10FarmExp(R$1000)	0.50±0.25	0.05	0.47±0.24	0.05	0.41±0.24	0.09	0.57±0.25	0.03	0.43±0.25	0.09	0.41±0.24	0.10	0.38±0.25	0.12
log10AgCred(R$1000)	-0.15±0.65	0.82	-0.15±0.65	0.82	-0.33±0.63	0.60	-0.15±0.64	0.82	0.03±0.67	0.96	-0.27±0.65	0.68	-0.12±0.64	0.85
FarmMixed	0.66±0.52	0.21	0.71±0.53	0.18	0.58±0.52	0.26	0.60±0.53	0.26	0.10±0.65	0.88	0.71±0.55	0.19	1.72±0.68	0.01
FarmPastureDom.	-0.17±0.64	0.79	-0.12±0.62	0.85	-0.31±0.63	0.63	-0.15±0.63	0.81	-0.49±0.82	0.55	-0.38±0.65	0.56	0.17±0.71	0.81
AgCooperativeYes	0.30±0.40	0.45	0.41±0.41	0.31	0.28±0.41	0.49	0.30±0.41	0.46	0.32±0.41	0.44	0.26±0.41	0.52	0.34±0.41	0.40
AgTrainingYes	-0.37±0.43	0.38	-0.26±0.43	0.54	-0.38±0.43	0.37	-0.33±0.43	0.44	-0.19±0.45	0.67	-0.02±0.44	0.96	-0.16±0.44	0.72
log10Soc.Sec(R$1000)	0.34±0.39	0.39	0.22±0.38	0.57	0.20±0.38	0.59	0.34±0.38	0.38	0.10±0.40	0.81	0.27±0.39	0.49	0.3±0.38	0.43
Municip.OuroVerde	0.2±0.51	0.70	0.22±0.50	0.66	0.16±0.49	0.75	0.19±0.50	0.70	0.36±0.53	0.50	0.03±0.50	0.95	0.11±0.5	0.83
Municip.PonteNova	1.3±0.53	0.01	1.37±0.53	0.01	1.44±0.54	0.01	1.44±0.54	0.01	1.41±0.56	0.01	1.63±0.56	0	1.5±0.55	0.01
Observations	186		186		186		186		187		187		187	
R2	0.133		0.127		0.124		0.132		0.152		0.142		0.134	

Table S8 continued. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current log_{10}(R$), total log_{10}(R$) and total (years) participation on the likelihood of household expenditure on Chemical pesticide (per hectare), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	PRONAF				**PAA**											
	Current (R$1000)		*Total (R$1000)*		*Current (R$1000)*		*Current (R$1000)*		*Current (R$1000)*		*Total (yrs)*		*Total (yrs)*		*Total (yrs)*	
	Model 8		*Model 9*		*Model 10*		*Model 11*		*Model 12*		*Model 13*		*Model 14*		*Model 15*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	-0.83±1.80	0.65	-1.3±1.62	0.42	-1.16±1.69	0.49	-0.92±1.67	0.58	-1.52±1.69	0.37	-0.56±1.70	0.74	-0.61±1.66	0.71	-2.11±1.74	0.22
Prog.Part.	1.19±0.93	0.20	-0.17±0.33	0.61	-0.28±0.53	0.60	-0.51±0.57	0.37	-0.56±0.58	0.33	**-0.37±0.13**	**0.004**	**-0.36±0.12**	**0.003**	0.25±0.14	0.08
Prog.Part.: FarmMixed	-1.55±1.08	0.15					**1.90±0.74**	**0.01**					**0.43±0.14**	**0.002**		
Prog.Part.: FarmPastureDom.	**-2.60±1.22**	**0.03**					**1.80±0.84**	**0.03**					0.33±0.18	0.07		
Prog.Part.: AgCooperativeYes					**1.54±0.64**	**0.02**					**0.43±0.15**	**0.003**				
Prog.Part.: log10Land(ha)									**1.30±0.51**	**0.01**						
Prog.Part.:Hsize															**-0.11±0.04**	**0.01**
Prev.Part.	-0.15±0.35	0.67			-0.17±0.08	0.04	-0.18±0.09	0.04	-0.16±0.09	0.06						
Oth.ZH.Curr.Part.	-0.06±0.21	0.77			-0.36±0.23	0.12	-0.29±0.22	0.19	-0.37±0.23	0.10						
Oth.ZH.Prev.Part.	0.01±0.05	0.91			0.04±0.05	0.49	0.02±0.05	0.77	0.03±0.05	0.62						
Oth.ZH.Total.Part.			-0.002±0.04	0.96							-0.01±0.05	0.88	-0.01±0.05	0.85	0.01±0.05	0.85
HHgenderMale	0.83±0.59	0.16	0.69±0.57	0.23	0.55±0.59	0.35	0.59±0.59	0.32	0.67±0.60	0.26	0.67±0.60	0.27	0.61±0.60	0.31	0.66±0.60	0.27
HHage	0.02±0.02	0.51	0.01±0.02	0.52	0.01±0.02	0.78	0.01±0.02	0.80	0.01±0.02	0.61	0.01±0.02	0.62	0.01±0.02	0.75	0.01±0.02	0.70
HHeducation	0.05±0.07	0.52	0.02±0.07	0.73	0.01±0.07	0.86	0.02±0.07	0.81	0.03±0.07	0.69	0.004±0.07	0.95	0.03±0.07	0.66	0.02±0.07	0.76
HHethnicityMixed	-0.06±0.52	0.91	0.01±0.50	0.99	0.20±0.52	0.70	0.25±0.53	0.63	0.14±0.53	0.79	0.34±0.52	0.51	0.33±0.52	0.53	-0.03±0.51	0.95
HHethnicityWhite	0.03±0.63	0.96	0.11±0.60	0.85	0.09±0.65	0.89	-0.02±0.66	0.97	-0.11±0.65	0.86	0.39±0.62	0.53	0.47±0.63	0.46	0.15±0.61	0.81
Hsize	-0.01±0.13	0.92	-0.01±0.13	0.94	0.02±0.14	0.86	-0.05±0.14	0.72	-0.03±0.14	0.81	0.01±0.14	0.95	-0.04±0.14	0.79	0.22±0.18	0.22
Poverty	0.03±0.17	0.84	0.04±0.17	0.83	0.002±0.18	0.99	0.08±0.19	0.67	0.09±0.19	0.63	0.06±0.19	0.76	0.11±0.18	0.53	0.04±0.18	0.81
log10Land(ha)	-0.08±0.39	0.84	0.02±0.38	0.96	0.004±0.41	0.99	0.04±0.40	0.92	0.13±0.41	0.75	0.10±0.41	0.80	0.21±0.42	0.62	0.04±0.39	0.93
Prop.Years	-0.01±0.02	0.70	-0.01±0.02	0.53	-0.01±0.02	0.52	-0.004±0.02	0.78	-0.01±0.02	0.50	-0.01±0.02	0.52	-0.001±0.02	0.93	-0.01±0.02	0.57
log10FarmExp (R$1000)	0.41±0.26	0.11	0.43±0.25	0.08	0.43±0.24	0.08	0.51±0.25	0.04	0.45±0.25	0.07	0.40±0.24	0.10	0.44±0.24	0.07	0.56±0.25	0.03
log10AgCred (R$1000)	-0.32±0.64	0.62	-0.27±0.63	0.67	-0.08±0.68	0.91	-0.002±0.70	1.00	-0.003±0.70	1.00	-0.29±0.68	0.67	-0.18±0.68	0.79	0.16±0.68	0.81
FarmMixed	-0.33±0.9	0.71	0.66±0.53	0.21	0.62±0.55	0.27	0.73±0.55	0.19	0.79±0.55	0.15	0.27±0.55	0.62	-0.54±0.67	0.42	0.82±0.55	0.13
FarmPastureDom.	-1.77±1.04	0.09	-0.16±0.61	0.79	-0.32±0.65	0.62	-0.35±0.65	0.59	-0.33±0.65	0.62	-0.51±0.66	0.44	-1.11±0.77	0.15	0.01±0.64	0.99
AgCooperativeYes	0.25±0.41	0.54	0.33±0.40	0.41	0.32±0.41	0.44	0.22±0.43	0.61	0.35±0.42	0.41	-0.66±0.52	0.21	0.11±0.42	0.79	0.26±0.41	0.53
AgTrainingYes	-0.19±0.45	0.68	-0.30±0.42	0.47	-0.25±0.44	0.57	-0.36±0.45	0.43	-0.28±0.44	0.53	0.003±0.44	0.99	-0.06±0.44	0.90	-0.13±0.44	0.77

log10Soc.Sec (R$1000)	0.24±0.39	0.53	0.24±0.38	0.53	0.30±0.40	0.46	0.21±0.41	0.60	0.17±0.40	0.66	0.25±0.39	0.52	0.23±0.40	0.57	0.35±0.38	0.35
Municip.OuroVerde	0.20±0.51	0.70	0.17±0.49	0.73	0.23±0.52	0.66	0.21±0.52	0.69	0.17±0.52	0.75	0.20±0.51	0.69	0.07±0.50	0.89	0.15±0.50	0.76
Municip.PonteNova	1.33±0.53	0.01	1.33±0.52	0.01	1.24±0.55	0.02	1.62±0.57	0.005	1.4±0.55	0.01	1.23±0.55	0.03	1.75±0.60	0.003	1.66±0.58	0.004
Observations	186		186		187		187		187		187		187		187	
McFadden R^2	0.133		0.103		0.15		0.16		0.157		0.148		0.151		0.13	

Table S9. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current log_{10}(R$), total log_{10}(R$) and total (years) participation on the amount of household expenditure (R$) on (log10 transformed) Inorganic fertilizer (per hectare), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	Zero Hunger				**Bolsa Familia**				**PRONAF**				**PAA**			
	Current (R$1000)		*Total (yrs)*		*Current (R$1000)*		*Total (yrs)*		*Current (R$1000)*		*Total (R$1000)*		*Current (R$1000)*		*Total (yrs)*	
	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*		*Model 7*		*Model 8*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	3.44±0.64	<0.01	3.67±0.64	<0.01	3.67±0.66	<0.01	3.65±0.64	<0.01	3.84±0.64	<0.01	3.71±0.65	<0.01	3.76±0.63	<0.01	3.66±0.64	<0.01
Prog.Part.	**-0.40±0.18**	**0.03**	0.02±0.02	0.16	-0.04±0.11	0.71	0.01±0.02	0.45	-0.28±0.15	0.07	0.001±0.11	0.99	-0.01±0.13	0.92	0.03±0.02	0.18
Prog.Part.: HHgenderMale	**0.46±0.20**	**0.02**														
Prev.Part.	0.02±0.02	0.27			0.02±0.02	0.39			0.06±0.11	0.60			0.03±0.03	0.26		
Oth.ZH.Curr.Part.					-0.01±0.10	0.94			0.01±0.08	0.87			-0.2±0.09	0.04		
Oth.ZH.Prev.Part.					0.03±0.02	0.17			0.03±0.02	0.15			0.04±0.02	0.07		
Oth.ZH.Total.Part.							0.03±0.02	0.17			0.02±0.02	0.17			0.02±0.02	0.40
HHgenderMale	-0.01±0.22	0.98	0.09±0.22	0.68	0.08±0.22	0.71	0.10±0.22	0.66	0.02±0.22	0.92	0.09±0.22	0.69	0.01±0.22	0.95	0.10±0.22	0.66
HHage	-0.01±0.01	0.16	-0.02±0.01	0.06	-0.02±0.01	0.07	-0.02±0.01	0.06	-0.02±0.01	0.03	-0.02±0.01	0.06	-0.02±0.01	0.03	-0.02±0.01	0.06
HHeducation	-0.001±0.02	0.95	-0.01±0.02	0.65	-0.01±0.02	0.58	-0.01±0.02	0.59	-0.01±0.02	0.54	-0.01±0.02	0.64	-0.02±0.02	0.49	-0.01±0.02	0.58
HHethnicityMixed	-0.18±0.23	0.45	-0.24±0.24	0.31	-0.25±0.24	0.30	-0.24±0.24	0.31	-0.28±0.24	0.25	-0.25±0.24	0.30	-0.24±0.23	0.30	-0.24±0.24	0.31
HHethnicityWhite	-0.55±0.25	0.03	-0.58±0.26	0.03	-0.58±0.26	0.03	-0.58±0.26	0.03	-0.61±0.26	0.02	-0.58±0.26	0.03	-0.62±0.26	0.02	-0.58±0.26	0.03
Hsize	-0.04±0.06	0.45	-0.07±0.06	0.23	-0.05±0.06	0.39	-0.05±0.06	0.40	-0.09±0.06	0.15	-0.07±0.06	0.23	-0.08±0.06	0.21	-0.05±0.06	0.39
Poverty	-0.05±0.07	0.47	-0.07±0.07	0.30	-0.07±0.07	0.36	-0.07±0.07	0.31	-0.08±0.07	0.28	-0.07±0.07	0.31	-0.07±0.07	0.32	-0.07±0.07	0.33
log10Land(ha)	-0.40±0.17	0.02	-0.44±0.17	0.01	-0.44±0.18	0.02	-0.44±0.17	0.01	-0.48±0.17	0.01	-0.46±0.18	0.01	-0.42±0.17	0.02	-0.45±0.17	0.01
Prop.Years	0.003±0.01	0.62	0.003±0.01	0.52	0.003±0.01	0.57	0.003±0.01	0.55	0.002±0.01	0.77	0.003±0.01	0.52	0.002±0.01	0.74	0.003±0.01	0.57
log10FarmExp (R$1000)	0.37±0.13	0.01	0.38±0.13	0.004	0.38±0.14	0.01	0.36±0.13	0.01	0.50±0.15	0.002	0.40±0.14	0.01	0.46±0.13	0.001	0.37±0.13	0.01
log10AgCred (R$1000)	-0.64±0.24	0.01	-0.60±0.25	0.02	-0.61±0.25	0.02	-0.61±0.25	0.02	-0.65±0.25	0.01	-0.61±0.25	0.02	-0.59±0.24	0.02	-0.62±0.25	0.01
FarmMixed	-0.44±0.18	0.02	-0.41±0.18	0.03	-0.43±0.19	0.03	-0.42±0.18	0.03	-0.41±0.19	0.03	-0.41±0.19	0.03	-0.45±0.19	0.02	-0.42±0.18	0.03
FarmPastureDom.	-0.77±0.27	0.01	-0.76±0.28	0.01	-0.76±0.28	0.01	-0.75±0.28	0.01	-0.79±0.28	0.01	-0.76±0.28	0.01	-0.85±0.28	0.003	-0.75±0.28	0.01
AgCooperativeYes	0.22±0.16	0.17	0.23±0.16	0.16	0.23±0.17	0.17	0.23±0.16	0.16	0.17±0.17	0.32	0.23±0.17	0.18	0.20±0.16	0.22	0.23±0.16	0.17
AgTrainingYes	-0.14±0.16	0.38	-0.21±0.16	0.19	-0.24±0.16	0.14	-0.22±0.15	0.17	-0.35±0.17	0.05	-0.22±0.16	0.18	-0.35±0.17	0.04	-0.23±0.16	0.16
log10Soc.Sec (R$1000)	0.17±0.15	0.26	0.21±0.15	0.17	0.19±0.15	0.22	0.20±0.15	0.20	0.24±0.15	0.12	0.22±0.16	0.17	0.18±0.15	0.23	0.20±0.15	0.19
Municip.OuroVerde	-0.25±0.20	0.22	-0.25±0.21	0.23	-0.2±0.23	0.37	-0.24±0.21	0.24	-0.08±0.22	0.73	-0.24±0.21	0.26	-0.08±0.22	0.72	-0.23±0.21	0.26
Municip.PonteNova	-0.20±0.16	0.21	-0.21±0.16	0.21	-0.22±0.16	0.18	-0.22±0.16	0.18	-0.16±0.16	0.32	-0.22±0.16	0.18	-0.19±0.16	0.23	-0.23±0.16	0.16
Observations	89		89		90		90		89		89		90		90	
R2	0.607		0.572		0.576		0.573		0.594		0.572		0.601		0.574	

Table S10. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current $\log_{10}$(R$), total $\log_{10}$(R$) and total (years) participation on the amount of household expenditure (R$) on (log10 transformed) Chemical pesticide (per hectare), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	Zero Hunger				**Bolsa Familia**			
	Current (R$1000)		*Total (yrs)*		*Current (R$1000)*		*Total (yrs)*	
	Model 1		*Model 2*		*Model 3*		*Model 4*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	2.16±0.54	<0.01	2.17±0.53	<0.01	2.18±0.54	<0.01	2.15±0.53	<0.01
Prog.Part.	0.004±0.06	0.95	-0.01±0.01	0.48	0.02±0.09	0.83	-0.02±0.02	0.32
Prev.Part.	-0.01±0.01	0.48			-0.02±0.02	0.29		
Oth.ZH.Curr.Part.					-0.02±0.09	0.82		
Oth.ZH.Prev.Part.					0.01±0.02	0.72		
Oth.ZH.Total.Part.							0.004±0.02	0.82
HHgenderMale	-0.07±0.21	0.73	-0.07±0.20	0.73	-0.06±0.21	0.78	-0.06±0.2	0.76
HHage	0.002±0.01	0.81	0.001±0.01	0.83	0.001±0.01	0.84	0.002±0.01	0.80
HHeducation	-0.02±0.02	0.24	-0.02±0.02	0.24	-0.03±0.02	0.21	-0.03±0.02	0.20
HHethnicityMixed	-0.003±0.16	0.99	-0.002±0.16	0.99	-0.01±0.16	0.96	-0.01±0.16	0.93
HHethnicityWhite	-0.03±0.19	0.87	-0.03±0.18	0.88	-0.03±0.19	0.88	-0.04±0.18	0.84
Hsize	0.07±0.04	0.09	0.07±0.04	0.09	0.07±0.04	0.08	0.08±0.04	0.06
Poverty	-0.14±0.05	0.01	-0.14±0.05	0.01	-0.14±0.05	0.01	-0.14±0.05	0.01
log10Land(ha)	-0.88±0.12	<0.01	-0.88±0.12	<0.01	-0.88±0.13	<0.01	-0.89±0.12	<0.01
Prop.Years	-0.004±0.005	0.36	-0.004±0.005	0.36	-0.005±0.005	0.35	-0.005±0.005	0.32
log10FarmExp(R$1000)	0.26±0.08	0.003	0.26±0.08	0.002	0.26±0.09	0.003	0.26±0.08	0.002
log10AgCred(R$1000)	0.005±0.23	0.98	0.01±0.23	0.96	-0.001±0.23	1.00	-0.003±0.23	0.99
FarmMixed	-0.04±0.16	0.81	-0.05±0.16	0.78	-0.07±0.17	0.66	-0.07±0.16	0.68
FarmPastureDom.	-0.37±0.20	0.07	-0.38±0.20	0.07	-0.38±0.20	0.07	-0.37±0.2	0.07
AgCooperativeYes	0.11±0.13	0.39	0.11±0.13	0.38	0.09±0.13	0.49	0.1±0.13	0.45
AgTrainingYes	0.06±0.13	0.65	0.06±0.13	0.64	0.02±0.13	0.87	0.02±0.13	0.87
log10Soc.Sec (R$1000)	-0.18±0.12	0.14	-0.18±0.12	0.14	-0.17±0.12	0.15	-0.18±0.12	0.14
Municip.OuroVerde	-0.03±0.16	0.87	-0.02±0.16	0.89	-0.02±0.17	0.91	-0.01±0.16	0.96
Municip.PonteNova	-0.23±0.14	0.11	-0.23±0.14	0.11	-0.22±0.14	0.12	-0.23±0.14	0.11
Observations	129		129		130		130	
R2	0.59		0.59		0.592		0.591	

Table S10 continued. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme current $\log_{10}$(R\$), total $\log_{10}$(R\$) and total (years) participation on the amount of household expenditure (R\$) on (log10 transformed) Chemical pesticide (per hectare), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	PRONAF				**PAA**			
	Current (R$1000)		*Total (R$1000)*		*Current (R$1000)*		*Total (yrs)*	
	Model 5		*Model 6*		*Model 7*		*Model 8*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept	2.10±0.54	<0.02	1.97±0.54	<0.04	2.18±0.53	<0.01	2.16±0.53	<0.01
Prog.Part.	-0.08±0.14	0.55	0.22±0.17	0.20	-0.09±0.12	0.44	-0.0002±0.02	0.99
Prog.Part.:FarmMixed			-0.05±0.19	0.78				
Prog.Part.:FarmPastureDom.			**-0.48±0.23**	**0.04**				
Prev.Part.	0.10±0.10	0.34			0.01±0.02	0.70		
Oth.ZH.Curr.Part.	-0.02±0.06	0.81			-0.03±0.07	0.65		
Oth.ZH.Prev.Part.	-0.01±0.01	0.42			-0.01±0.02	0.53		
Oth.ZH.Total.Part.			-0.01±0.01	0.34			-0.01±0.01	0.49
HHgenderMale	-0.07±0.21	0.75	-0.08±0.2	0.69	-0.06±0.21	0.77	-0.06±0.21	0.75
HHage	0.001±0.01	0.92	0.002±0.01	0.73	-0.0001± 0.01	0.96	0.002±0.01	0.81
HHeducation	-0.02±0.02	0.24	-0.02±0.02	0.28	-0.03±0.02	0.22	-0.03±0.02	0.23
HHethnicityMixed	-0.003±0.16	0.99	-0.06±0.16	0.71	-0.01±0.16	0.95	-0.01±0.16	0.93
HHethnicityWhite	-0.03±0.19	0.89	-0.01±0.18	0.93	-0.01±0.19	0.97	-0.04±0.18	0.84
Hsize	0.07±0.04	0.09	0.09±0.04	0.02	0.07±0.04	0.09	0.07±0.04	0.09
Poverty	-0.14±0.05	0.01	-0.12±0.05	0.02	-0.14±0.05	0.01	-0.14±0.05	0.01
log10Land(ha)	-0.9±0.13	<0.01	-0.93±0.13	<0.01	-0.87±0.13	<0.01	-0.88±0.12	<0.01
Prop.Years	-0.004±0.005	0.37	-0.005±0.005	0.29	-0.004± 0.005	0.41	-0.004±0.005	0.34
log10FarmExp(R$1000)	0.24±0.09	0.01	0.24±0.09	0.01	0.28±0.08	0.001	0.27±0.08	0.002
log10AgCred(R$1000)	0.02±0.23	0.95	0.09±0.23	0.70	0.03±0.23	0.89	0.002±0.23	0.99
FarmMixed	-0.08±0.17	0.65	-0.04±0.23	0.85	-0.09±0.17	0.58	-0.06±0.16	0.71
FarmPastureDom.	-0.41±0.21	0.06	0.04±0.28	0.88	-0.39±0.21	0.07	-0.38±0.20	0.07
AgCooperativeYes	0.12±0.13	0.37	0.14±0.13	0.28	0.10±0.13	0.43	0.11±0.13	0.42
AgTrainingYes	0.03±0.14	0.83	0.04±0.13	0.75	0.04±0.13	0.76	0.03±0.13	0.81
log10Soc.Sec (R$1000)	-0.18±0.12	0.14	-0.17±0.12	0.15	-0.16±0.12	0.17	-0.17±0.12	0.16
Municip.OuroVerde	-0.001±0.17	0.99	-0.06±0.16	0.69	0.02±0.17	0.93	-0.005±0.16	0.98
Municip.PonteNova	-0.20±0.15	0.17	-0.24±0.14	0.09	-0.24±0.15	0.10	-0.23±0.14	0.12
Observations	129		129		130		130	
R2	0.596		0.613		0.592		0.589	

Table S11. Effect of Zero Hunger overall, Bolsa Familia, PRONAF and PAA programme total log$_{10}$(R$) and total (years) participation on Natural vegetation loss (none = ha, little = > 0 to 1 ha, high = > 1 ha) between 2003 and 2016 (Overall) and from the first year of programme participation (from 2003 for non-participants) (Targeted), showing all model coefficients ± standard errors and significance (P). Estimates in grey correspond to programme participation and programme-covariate interactions, with significant estimates highlighted in bold

	Zero Hunger				**Bolsa Familia**				**PRONAF**				**PAA**			
	Overall		***Targeted***		***Overall***		***Targeted***		***Overall***		***Targeted***		***Overall***		***Targeted***	
	Total (yrs)		*Total (yrs)*		*Total (yrs)*		*Total (yrs)*		*Total (R$1000)*		*Total (R$1000)*		*Total (yrs)*		*Total (yrs)*	
	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*		*Model 7*		*Model 8*	
Coefficients	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P	Coef±S.E.	P
Intercept:None|Little	1.81±2.19	0.41	2.59±2.60	0.32	1.44±2.24	0.52	1.74±2.74	0.52	1.95±2.20	0.38	2.73±2.72	0.31	1.72±2.24	0.44	3.68±2.48	0.14
Intercept:Little|A lot	2.66±2.20	0.23	3.33±2.61	0.20	2.33±2.25	0.30	2.72±2.75	0.32	2.79±2.21	0.21	3.58±2.74	0.19	2.60±2.25	0.25	4.53±2.50	0.07
Prog.Part.	-0.11±0.05	0.05	-0.03±0.06	0.63	-0.38±0.53	0.47	2.02±1.19	0.09	-0.05±0.08	0.55	-0.01±0.10	0.89	-0.06±0.09	0.53	**-0.23±0.10**	**0.02**
Prog.Part.: log10Soc.Sec(R$1000)					**1.17±0.56**	**0.04**										
Prog.Part.:Hsize							**-0.7±0.34**	**0.04**								
Prog.Part.: AgTrainingYes													**-0.36±0.17**	**0.03**		
Oth.ZH.Total.Part.					-0.14±0.06	0.03	-0.13±0.07	0.08	-0.12±0.07	0.06	-0.17±0.09	0.07	-0.06±0.07	0.43	-0.07±0.08	0.37
HHgenderMale	-0.63±0.76	0.41	-1.20±0.83	0.15	-0.69±0.82	0.40	-0.51±0.91	0.58	-0.57±0.77	0.46	-1.13±0.87	0.20	-0.55±0.79	0.49	-1.01±0.80	0.21
HHage	-0.02±0.03	0.61	-0.01±0.03	0.78	-0.02±0.03	0.50	-0.04±0.04	0.28	-0.01±0.03	0.67	0.02±0.04	0.62	-0.02±0.03	0.51	0.005±0.03	0.88
HHeducation	-0.04±0.09	0.69	-0.03±0.10	0.75	-0.03±0.10	0.74	-0.17±0.12	0.15	-0.04±0.09	0.66	-0.07±0.11	0.53	-0.07±0.09	0.45	-0.01±0.10	0.95
HHethnicityMixed	0.77±0.78	0.33	1.01±0.98	0.30	0.74±0.80	0.35	0.56±0.92	0.54	0.76±0.79	0.34	-0.06±0.88	0.94	0.60±0.82	0.47	1.14±0.94	0.23
HHethnicityWhite	1.69±0.87	0.05	1.54±1.06	0.15	1.88±0.88	0.03	1.49±1.01	0.14	1.66±0.87	0.06	0.83±0.95	0.38	1.68±0.90	0.06	2.12±1.02	0.04
Hsize	0.14±0.17	0.40	0.08±0.20	0.69	0.22±0.18	0.23	0.55±0.23	0.02	0.16±0.17	0.34	0.28±0.20	0.16	0.20±0.18	0.26	0.30±0.19	0.12
Poverty	-0.16±0.19	0.40	-0.21±0.22	0.34	-0.11±0.21	0.61	-0.15±0.22	0.49	-0.15±0.19	0.45	-0.27±0.23	0.24	-0.10±0.20	0.64	-0.07±0.22	0.76
log10Land(ha)	-0.70±0.55	0.20	-0.65±0.64	0.30	-0.81±0.58	0.16	-0.81±0.65	0.21	-0.70±0.56	0.21	-1.17±0.73	0.11	-0.63±0.57	0.27	-1.08±0.67	0.11
Prop.Years	-0.01±0.02	0.79	-0.02±0.02	0.40	-0.01±0.02	0.70	0.01±0.02	0.82	-0.01±0.02	0.70	-0.04±0.02	0.06	-0.01±0.02	0.52	-0.01±0.02	0.72
log10FarmExp (R$1000)	0.46±0.35	0.19	0.45±0.40	0.27	0.45±0.39	0.24	0.79±0.46	0.08	0.45±0.36	0.20	0.33±0.40	0.41	0.43±0.37	0.24	0.40±0.38	0.29
FarmMixed	0.97±0.66	0.14	1.17±0.80	0.15	0.88±0.70	0.21	0.97±0.80	0.23	0.86±0.67	0.20	1.68±0.95	0.08	0.70±0.67	0.30	1.77±0.83	0.03
FarmPastureDom.	-0.63±1.07	0.56	0.13±1.19	0.92	-0.63±1.10	0.56	0.08±1.16	0.95	-0.67±1.07	0.53	1.04±1.34	0.44	-0.77±1.10	0.48	0.49±1.20	0.68
AgCooperativeYes	1.14±0.59	0.05	1.24±0.72	0.09	1.39±0.62	0.03	1.10±0.67	0.10	1.12±0.59	0.06	1.46±0.81	0.07	1.14±0.61	0.06	1.10±0.68	0.11
AgTrainingYes	0.40±0.53	0.44	0.01±0.63	0.98	0.49±0.54	0.36	-0.29±0.67	0.67	0.18±0.54	0.75	0.25±0.68	0.71	1.10±0.71	0.12	0.27±0.62	0.66
log10Soc.Sec (R$1000)	-0.37±0.50	0.46	-0.23±0.6	0.70	-1.51±0.75	0.04	-0.79±0.61	0.20	-0.35±0.50	0.49	-0.09±0.63	0.88	-0.35±0.52	0.50	-0.65±0.56	0.25
Municip.OuroVerde	1.05±0.60	0.08	1.21±0.67	0.07	0.95±0.61	0.12	1.77±0.74	0.02	1.13±0.60	0.06	0.67±0.71	0.35	1.14±0.62	0.07	1.00±0.68	0.14
Municip.PonteNova	-0.4±0.61	0.52	-0.41±0.79	0.60	-0.49±0.64	0.44	-0.23±0.76	0.77	-0.42±0.62	0.51	-0.95±0.83	0.25	-0.42±0.64	0.51	-0.18±0.69	0.80
Observations	185		185		185		185		186		186		186		186	
R2	0.13		0.135		0.164		0.176		0.128		0.174		0.165		0.154	

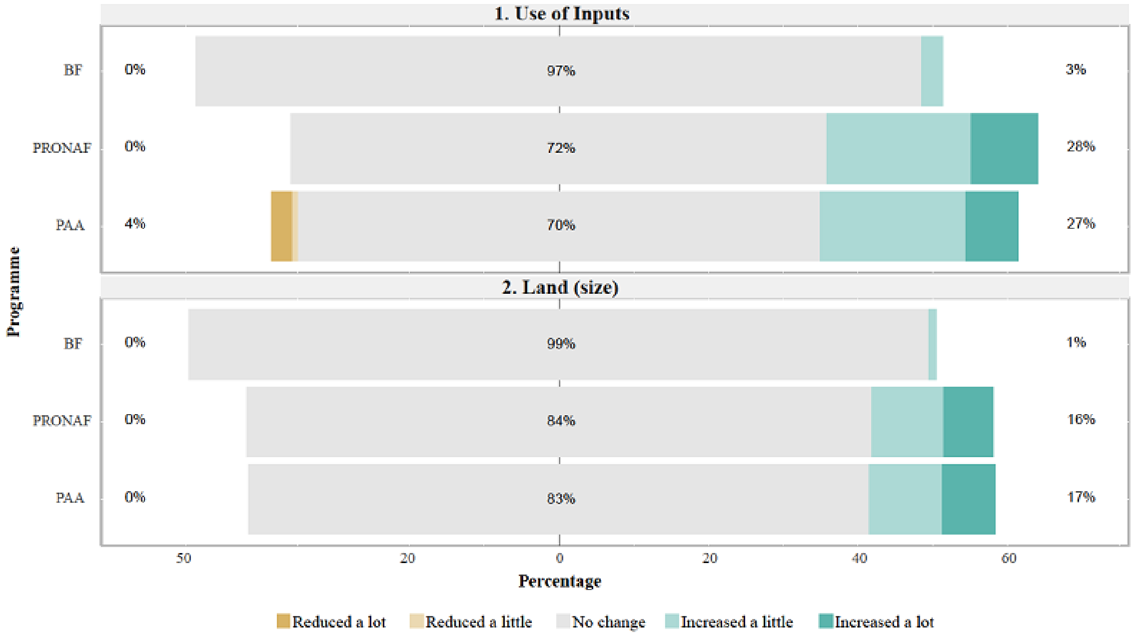

Figure S1. Self-reported impact of programme participation on farming practices (use of inputs and size of land area), showing proportion of negative impact (reduced a lot and reduced a little), positive impact (increased a little and increased a lot), and neutral replies, by main Zero Hunger component (Bolsa Familia (BF), PRONAF and PAA)

Chapter 4

The Impacts of the Nationwide Environmental Registry on Land Use in Brazil

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Abstract

The nationwide rural environmental registry (CAR) program in Brazil can facilitate monitoring of people's land use and enforce environmental regulations. However, existing studies have primarily attended to deforestation, thereby creating a blind spot with respect to impacts on land use. In this paper, we estimate the impacts of CAR enrollment rates on crop and pasture area in the states of Pará and Mato Grosso. We show that while the CAR did not have any significant impact on crop area, it slowed pasture expansion on large-scale farms and led to pasture expansion on small-scale farms. We find that access to rural credit and sales of cattle to major slaughterhouses – both of which were facilitated by CAR registration – might have contributed to the heterogeneous impacts. Our results provide insights for conservation and development policies as we illuminate how the intended environmental objectives of land registry programs might be undermined by credit policies.

Keywords: Land use change; Pasture area; Environmental monitoring; Credit access; Small-scale farmers

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1. Introduction

Environmental regulations alone do not guarantee environmental protection. Often, governments lack the capacity and tools to monitor people's land use behaviors and enforce environmental regulations, especially in developing countries. Registration and spatial referencing of owned or occupied land can be a critical first step to facilitating monitoring on private properties. Indeed, Brazil has mandated geo-referencing and identification of all property boundaries, Legal Reserves, and Areas of Permanent Preservation through the implementation of a national *Cadastro Ambiental Rural* (the Rural Environmental Registry – CAR) (Azevedo et al. 2017). The CAR, introduced in 2006 but mandated in 2012 in the revised federal environmental regulation called the Forest Code (Federal Law 12,615/2012), explicitly aims to decrease deforestation and environmental degradation by facilitating monitoring and enforcement.

Estimates of the impacts of the CAR on deforestation have shown mixed results (Alix-Garcia et al. 2018; Azevedo et al. 2017; Kröger 2016; L'Roe et al. 2016). These inconclusive findings may be partially explained by a) a long implementation period, in which deadlines to comply have been extended numerous times, and b) limitations on data access - data did not become fully public until 2016 (Roitman et al. 2018), though some limited datasets were available earlier (Richards and Van Wey 2016). Thus far, evidence suggests that the CAR has done little to slow overall deforestation rates (Azevedo et al. 2017; Kröger 2016), except on certain types of small-scale farm properties (L'Roe et al. 2016). However, other research identified a decrease in deforestation associated with enrollment in the CAR when compared with properties that were similarly motivated to participate in the CAR (Alix-Garcia et al. 2018). Still, the implementation of the CAR and publication of CAR data have allowed unprecedented insight into characteristics of Brazilian rural properties and into levels of Forest Code compliance (Richards and Van Wey 2016; de Freitas et al. 2017; Assunção et al. 2017). Because of the sheer size of the Brazilian territory and the significance of Brazil's forest, in particular the Amazon, for climate change mitigation effects, the outcomes of these ongoing environmental initiatives are of global significance (Lahsen et al. 2016).

In this paper, we address two central questions: a) How do farmers change their land use strategies related to crop and livestock production after registering for the CAR, and b) What are the mechanisms driving any significant changes in areas under crop and livestock production? To answer these questions, we first discuss how the CAR might affect farmers' land use decisions by identifying factors that affect people's land use decisions and by aggregating land use changes up to the municipality level to capture aggregate impacts of CAR registration on land use within municipalities. Based on the discussion of the model, we empirically estimate a causal relationship between yearly variations in total area under CAR registration and variations in area under crop production and pasture by using a dynamic land use model. We apply Arellano and Bond GMM estimators to a panel dataset of the Amazonian states of Pará (PA) and

Mato Grosso (MT) in order to address endogeneity issues. These two states are well suited for our analysis as their implementation of the CAR began earlier than in the rest of Brazil. We address selection bias issues by creating and using Covariate Balancing Generalized Propensity Score (CBGPS) weights that explicitly correct for the potential bias arising from the likely non-random selection of CAR registration in municipalities. We investigate heterogeneous impacts of CAR registration by average CAR property size and associated impacts of the size of CAR registration area on credit use in order to identify causal mechanisms. We also test the robustness of our results by controlling for the data quality.

Our results suggest that CAR registration did not have any significant impacts on (annual) change in area under crop production but had significant negative impacts on changes in area under pasture. Although the overall impact was negative, with pasture area growing at a slower rate the greater CAR coverage per municipality, this impact was most pronounced on municipalities dominated by large properties (> 300 ha average). By contrast, we find that increased CAR area has caused more rapid pasture expansion in municipalities with a smaller average CAR property size (<300 ha). We find evidence that changing access to credit could be one mechanism behind varied rates of pasture expansion, as pasture dominated municipalities with smaller (larger) average CAR property size used significantly more (less) credit as the CAR registered area increased. This finding is supported by evidence showing that farmers in municipalities with more small-scale properties and higher Forest Code compliance rates used significantly more credit as the area registered for the CAR increased compared to municipalities with lower compliance rates.

Our study complements existing literature in showing significant and/or heterogeneous impacts of the CAR on land use types (cropland and pasture area) (e.g., Alix-Garcia et al. 2018; L'Roe et al. 2016), and showing that CAR registration has been used to determine market and credit access (Alix-Garcia and Gibbs 2017; Assunção et al. 2017b), though these themes have not yet been fully explored. Importantly, our results offer information on potential mechanisms underlying relations between the CAR and land use – findings which have specific policy implications. In particular, our investigation of the relationship between the CAR and credit use indicates that small-scale farmers used more credit after registering for the CAR, suggesting that the formalization offered by CAR registration could have encouraged small-scale farmers to gain access to credit and expand their pasture area (Rasmussen et al. 2017). In contrast, we find evidence suggesting that medium- and large-scale farmers might have had restricted access to credit, which could have limited their expansion of pasture area. The finding that medium- and large-scale cattle ranchers reduced the expansion of pasture area as the CAR area increased may also reflect the impacts of the zero-deforestation agreement in addition to the government's credit policy.

2. Background

Monitoring and enforcement using the CAR in Brazil

While the CAR was implemented nationally in 2012, environmental registries began several years earlier in the states of PA (2006) and MT (2009). To register, land owners declare their property boundaries in an online portal, which later passes through a series of verification steps. Since the federal system was implemented, the initial declaration step takes place online and the initial CAR is issued automatically, if provisionally, which is similar to how the system worked in the state of PA. Under the MT state system, some verification by the state took place before the CAR was issued. Land owners with deficiencies in their compliance with the Forest Code, including insufficient Legal Reserve area, sign an agreement stating that they will follow a plan to replant or allow the degraded area to regrow, and in some cases they have the option to compensate their deficiencies off property.

As part of the push to encourage registration, the use of the CAR for enforcement of environmental regulations has been delayed (Azevedo et al. 2017), although the CAR registration database has been used by farmers to provide evidence for compliance with environmental laws and by major commodities traders in the soy and beef sectors to help monitor ongoing deforestation (Rausch and Gibbs 2016; Gibbs et al. 2015). In 2008, Central Bank Resolution 3545 required proof of legal compliance with the Forest Code in order to grant access to rural credit, i.e. the National Rural Credit System (SNCR). The SNCR is used by Brazilian farmers and ranchers to access low interest credit lines for agricultural production activities such as crop and livestock operations, purchasing of inputs, and marketing of products. Although small-scale farmers have been exempted from presenting some documents including proof of legal compliance[5], CAR registration has become one of major means to prove whether a property was in compliance with the Forest Code. In 2012, the revised Forest Code also mandated the banks to require farmers to be registered for the CAR to receive rural credit (Latawiec et al. 2017).

CAR registration and land use trends

In PA and MT, the area registered in the CAR increased between 2011 and 2015, while the average size of the properties registering decreased (Figure 1). By 2015, 49% of CAR-eligible areas[6] in PA and 78% of

[5] See Assunção et al. (2016) for a detailed discussion on exemptions for different types of small-scale farmers.
[6] Areas eligible for CAR registration are limited to those that are privately owned or are eligible for private ownership, which excludes areas such as protected areas and certain types of settlement projects where individual CARs are not permitted.

eligible areas in MT had been registered. Both states experienced an increase in area registered between 2011 and 2015. Most noticeably there was a large spike in registration in MT after 2014, which is when CAR was first legislated, with a registration deadline of May 2015; 53% of total eligible area in MT was registered in 2015. At the same time the average CAR property size reduced drastically in MT, suggesting an increase in smaller-scale farms registered during this time period. Still the average CAR property size remained large in MT, at 610 ha in 2015, particularly compared to PA which dropped to an average of 210 ha, i.e. almost 100 ha below the threshold of what is considered a small-scale farmer in these two states.

During the same period, by far the largest increase in crop area took place in MT, with an increase of ~4.2 million ha compared to only ~0.3 million ha in PA. The increase in pasture area was similar in both states, with ~1.6 million ha and ~2.1 million ha in MT and PA, respectively.

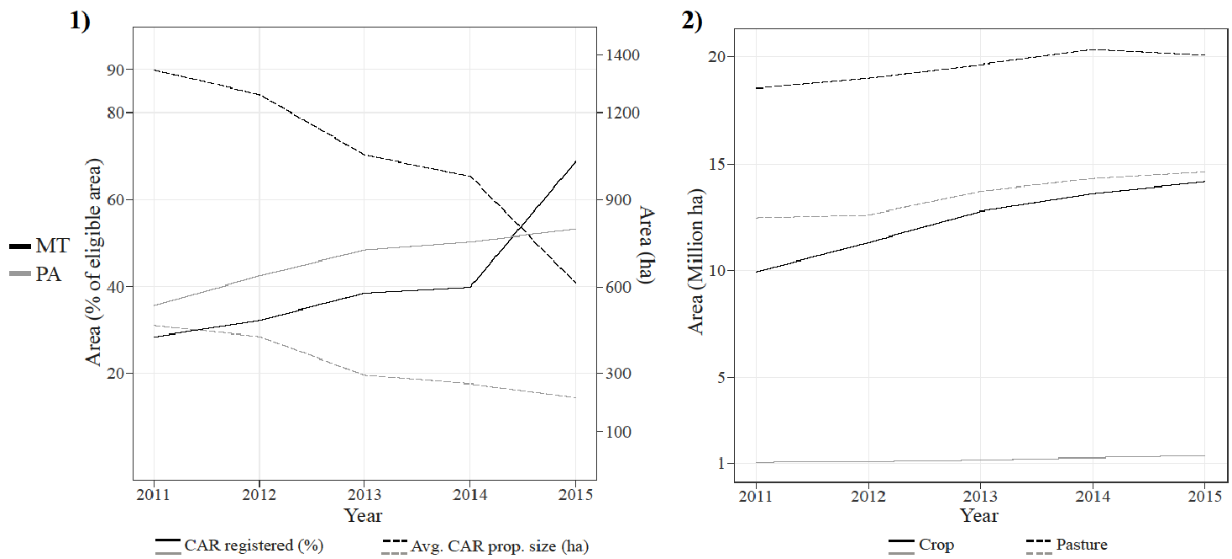

Figure 1. Changes in 1) Area registered under the CAR (total and avg. CAR property size), and 2) Total crop and pasture area, for 2011-2015 for Pará (PA) and Mato Grosso (MT)

Notes: CAR registered area and avg. CAR property (panel 1) are expressed on two different scales, the left Y-axis refer to CAR registered area in % while the right Y-axis refer to avg. CAR property size in hectare

3. Conceptual framework

Hypothesized impacts of the CAR on farmers' land use decisions

CAR registration at current time period will change farmers' land use in the same period or in the following periods if the land constraint imposed by the CAR registration is binding and/or if it changes a farmer's ability or profitability in crop/livestock production[7]. Here, we discuss two major mechanisms through which the CAR might affect farmers' land use decisions: monitoring/enforcement and credit access.

One of the most critical mechanisms that could make CAR registration a binding constraint in farmers' land use is monitoring and enforcement of environmental regulations, whether by the government, NGOs, or private companies, with registered CAR boundaries (Rudorff et al. 2012; Vieira et al. 2014; Börner et al. 2015). If we assume perfect monitoring with a heavy penalty for clearing forest, farmers who would clear natural vegetation without the monitoring and enforcement may choose not to clear. Their crop or pasture area might stay the same or decrease in which case we will see reduced growth in the amount of area under production or lower amount of area under production in the municipalities with higher CAR registration rates. Under imperfect monitoring or if the violation penalty is not high enough, the farmers whose expected marginal profit from clearing is positive will continue to clear even though they already have cleared more area than what is legally permitted by the Forest Code. In this case, CAR registration will not have any significant impact on the total amount of crop or pasture area.

CAR registration can also impact the amount of crop or pasture area by mediating farmers' credit access. As discussed in the background section, proof of legal compliance with the Forest Code is required for obtaining credit and CAR registration became a way to provide such proof. Also, CAR registration became mandatory for credit access in 2012. Credit access directly affects farmers' ability to clear and intensify. We expect the total amount of land area under crop or livestock production to increase as a result of CAR registration if it has lowered the barriers for some farmers for demonstrating environmental compliance and be granted access to credit.

However, the impact of credit is likely to vary depending on two factors: 1) whether a property is small-scale or not and 2) the legal compliance status of a property. Small-scale farmers who traditionally had less access to credit might have been able to obtain or maintain access to credit after CAR registration, depending on the legal compliance status of the property, following changes in the credit policy in 2008 and 2012. Alternatively, farmers whose properties had native vegetation cover above the legal compliance limit, and were made aware of that as a result of registering for the CAR, may clear more until reaching the lower limit, with proper licensing, which may result in an increasing crop or pasture area (Jung et al. 2017; Rasmussen et al. 2017). If they use this credit to invest in their production system, this might include further clearing to expand their production area (Fitz 2018). Therefore, CAR registration might on the one hand lead to increased amount of crop or pasture area within a municipality if the bulk of properties have more land under native vegetation than what is legally required and/or if there are more small-scale farmers. On the other hand, medium or large-scale farmers with a native vegetation area below the legal limit are more

[7] Please see the *Appendix* for the identification of factors that affect land use outcomes.

likely to be penalized and excluded from accessing rural credit, which may result in a reduction in crop or pasture area. However, as larger-scale farmers tend to have more financial options available to them, credit restrictions imposed by the Central Bank might be less influential to land use decisions for these farmers.

In sum, we expect the CAR to have significant impacts on crop or pasture area if there is any monitoring or enforcement efforts by the government and/or private initiatives that impose a binding constraint for farmers upon registering for the CAR. However, the impacts will vary depending on the legal compliance status of properties and whether a property is small-scale or not, which changes credit sources and access rules imposed by the government.

4. Methods and data

Land use is a dynamic process in which factors that have affected previous year's land use are likely to affect current year's land use. We account for this by using the previous year's land use as a determinant of the current year's land use (see *Appendix*). The inclusion of the previous year's land use to estimate the current year's land use makes it challenging to obtain consistent parameters because of the endogeneity problem. We use Arellano and Bond (1991) generalized method of moments (GMM) estimator that addresses this issue by using past values of endogenous variables as well as exogenous variables as instruments. Our use of this model also deals with an endogenous nature of other variables including the area registered for the CAR and other socioeconomic and institutional factors such as monitoring and the amount of credit use assumed to affect land use.

We estimate changes in the total area under crop and pasture according to rates of increase in the amount of CAR-eligible area registered for the CAR[8]. Our dataset consists of a panel of 283 municipalities within PA and MT from 2011 to 2015.[9] We focus on the years from 2011 to 2015, which are the years for which the information on the snapshot of total properties registered in a given year is available[10]. We explicitly model the non-random nature of the area under the CAR in each municipality using data from 2006, which is when the CAR registration was limited and therefore minimizes the bias. We do this by generating CBGPS weights that minimize the correlation between the area under the CAR and "pre-

[8] We find that estimation results using the total area as variables are not driven by outliers from largest or smallest municipalities due to the low correlation (0.26) between changes in the area under the CAR and the size of municipalities over our study time period (2011-2015). Also, the main results from using the total area do not change when using percentages as variables.

[9] The total number of 283 municipalities is after excluding two municipalities with inconsistent covariates and no CAR-eligible area. One municipality split during our time span, which we subsequently aggregate back together.

[10] Using the information about properties' year of registration, included as an attribute in the CAR datasets from which the number of properties registered each year was calculated, could stretch the years to before 2011, but it will introduce bias resulting from measurement errors because properties sometimes become unregistered, which will not be reflected for the data before 2011.

treatment" covariates and run the same GMM models using the weights. We investigate heterogeneous impacts of CAR registration by property size and potential mechanisms underlying relations between the CAR and land use by testing the relationship between the CAR and credit. Lastly, we check the robustness of our results by controlling for the data quality of our land use data by running the same models with municipalities that have better data quality. We discuss in detail the methods and data used in the following sections.

Dependent variables: crop and pasture area

Our main dependent variables of interest are crop and pasture area. We obtain data on temporary and permanent crop area from the municipal agricultural production survey (PAM) from the Brazilian Institute of Geography and Statistics (IBGE, 2016)[11], and combine them to create total crop area. When analyzing the impact of CAR registration on pasture area, we use MapBiomas as this is the only available annual data on pasture area. We find consistency in pasture area detection with the biannual TerraClass dataset (Table A1 in the Appendix), which is an official land cover data produced by the Brazilian government. In order to address data quality issues with the MapBiomas data, we test the robustness of our results by running the same models on a set of restricted samples with better data quality ranging from 1,127 to 291 observations (see section 5.3).

Area registered for the CAR and other CAR related variables

Our main variable of interest, total area registered under the CAR per municipality, is created using CAR property maps downloaded over time from State Environmental agencies (SIMLAM-MT; SMILAM – PA). Some areas are not eligible for CAR registration, including most federal and state protected areas, and indigenous areas. To determine the eligible CAR area in each municipality, we overlay maps of these non-eligible areas, state and federal conservation units (ICMBio 2016) and indigenous territories (FUNAI 2017), and remove them from the total area of the municipality. We then intersect this map of eligible portions of municipalities with each year's CAR property map and sum the registered area in each municipality which falls within eligible CAR area to determine the total CAR area for that year. Compliance with the Forest Code is determined using PRODES and is based on the most common legal reserve requirement of 80% of

[11] Annual crop area is also available from the MapBiomas dataset (MapBiomas, 2017). The version of MapBiomas used in this paper (v2.3) is shown to have high overall accuracy (82.4% for the Amazon and 88.3% for the Cerrado), however, when comparing the crop area detected by MapBiomas to IBGE and the biannual TerraClass dataset (Table A1) we find a limited ability of MapBiomas to detect crop area particularly in PA, and therefore we rather use IBGE data when testing the impacts of CAR on total crop area.

the property in the Amazon biome and 35% for Cerrado municipalities in the Legal Amazon, though some properties' requirements may be lower (Soares Filho et al. 2014). Our estimates for compliance are approximate, as we do not consider components of Forest Code compliance beyond Legal Reserves for which data are not available. For example, we do not consider whether previous clearing outside of the Legal Reserve was done with a license, leading us to overestimate "compliance" in some cases. In addition, we do not consider if excess clearing has been compensated off property or if the land owner has begun reforestation efforts; in these cases we would have underestimated compliance.

Other covariates: socioeconomic and biophysical data

To capture variability in physical constraints, e.g., transportation costs, and market conditions, identified as P_{ijt} and B_{ijt} in the *Appendix*, we create an index of real prices for rice, corn, cassava, soybean, sugarcane and cattle for 2011-2015 following Assunção et al. (2017b). We omit corn prices from the analysis given its high correlation to sugarcane and rice prices (r = 0.43 and 0.49, respectively). Annual precipitation is gathered from U.S. National Oceanic and Atmospheric Administration (NOAA 2018), which measures total annual rainfall per 1 km^2. We average the values for the cells within each municipality.

The vector of socioeconomic characteristics include fine intensity and credit density. Following Hargrave and Kis-Katos (2013), we calculate the fine intensity by taking total value of fines issued in a municipality (IBAMA, 2017) divided by the amount of natural vegetation removed from MapBiomas in a given year. Credit density is calculated by dividing the total financial value of rural credit obtained per municipality per year from the Brazilian Central Bank (Banco Central do Brasil 2017) by the total crop and pasture area from MapBiomas. We extract total protected areas, i.e. all areas categorized as strictly protected areas, sustainable use areas and indigenous areas, per year per municipality from the World database on Protected Areas (www.wdpa.org). Our measure of municipal GDP per capita and population density per year come from IBGE (2015). Table 1 column (1) lists all variables and their descriptive statistics used for the main results (based on the dynamic model) (see section 4.4), while column (2) lists those used to create the CBGPS weights to adjust for possible selection bias (see section 4.5 for detailed description).

Table 1. Descriptive statistics

Variable	Definition	Mean (SD)	
		Dynamic (2011-2015)	CBGPS (2006)
Land use variables			
Crop area (ha)	Total crop area from Mapbiomas data	47,864 (115,992)	29,373 (57,049)
Pasture area (ha)	Total pasture area from Mapbiomas data	117,000 (143,200)	116,128 (141,883)
CAR-related variables			
CAR area (ha)	Total area registered for CAR 2011-2015	201,616 (270,385)	
Forest Code compliance (%)	The percentage of the number of Forest Code compliant CAR properties over total number of CAR properties	22 (27)	
Avg. property size of CAR registered properties (ha)	Total area under the CAR divided by the total number of CAR properties	1,070 (1,958)	
Socioeconomic variables			
Avg. property size (ha)	Total area under farming divided by the total number of properties in 2006 from the Census data		387 (598)
Credit density (BRL/ha)	Total credit value divided by total area under agricultural production	267 (579)	128 (345)
Fine intensity (BRL/ha)	Total environmental fines divided by total area under natural vegetation	8,133 (67,330)	2,168 (20,102)
Crop prices	Area-weighted prices of rice, sugarcane, cassava, and soybean, following Assunção et al. (2015; 2017)	0.13; 0.11; 0.73; 1.11 (0.24; 0.45; 1.69; 2.42)	0.11; 0.11; 0.39; 0.81 (0.2; 0.44; 0.88; 1.66)
Cattle price	Area-weighted price of cattle following Assunção et al. (2015; 2017)	17.48 (17.73)	11.48 (11.59)
GDP per capita (BRL)	Total GDP divided by population	19 (19)	7 (7)
Pop. Density	Total population per km^2	32 (186)	31 (189)
Protected area (ha)	Total area under strict + sustainable use + indig. Land	300,900 (1,221,500)	
Biophysical variables			
CAR eligible area (ha)*	Total eligible area, following Alix-Garcia et al. (2018)		461,839 (487,638)
Precipitation (mm)	annual total avg. (avg. annual mm/1 square km)	2,205 (646)	

Precipitation (mm)	long-term avg. (>25 years between 1950-1990) (avg. mm/month)	192 (41)
Elevation (m)*	Average elevation within each municipality	232 (168)
Slope (degree)*	Average slope within each municipality	6 (1)
Remoteness (time)	Min. travel time from the centroid of municipality to the nearest city with pop => 50,000 (for year 2010)	431 (691)

Note: N = 1,414 observations for 283 municipalities. Dynamic (1) indicate annual variables spanning 2011-2015 used in the dynamic models (see empirical strategy section 4.4). CBGPS (2) indicate variables used to make the covariate balancing weights to control for selection bias, and use values from year 2006 if not otherwise specified in the description or indicated as time-invariant by asterisk (*). Commodity prices are the Paraná-based real commodity prices in semester/year *t* weighted by average commodity area/n heads for year 2004 and 2005 following Assunção et al. (2017b)

Dynami model using panel data

The dynamic nature of our dependent variable necessarily creates correlation between the regressors and the error term. In addition, many factors including our main variable of interest, CAR area, and other covariates such as credit and fine density are likely to be endogenously determined. We use Arellano and Bond (1991) GMM estimator with a two-step Windmeijer (2005) bias-correction, which takes differences of dependent and independent variables for the estimation and use past values of endogenous variables as well as exogenous variables as instruments for endogenous variables including the lagged dependent variable. We use separate instruments for each time period.

We estimate the following regression equation as specified in equation (1).

(1) $$\Delta E_{jt}^{k} = \beta_1 \Delta E_{jt-1}^{k} + \delta \Delta CAR_{jt-1} + \theta \Delta CAR_{jt} + X_{jt}\beta + \gamma_t + \varepsilon_{jt}$$

where E_{jt}^{k} and E_{jt-1}^{k} indicate the total amount of area under *k* (*k*=*crop* or *pasture*) in a municipality *j* at time period *t* and *t-1*, respectively; CAR_{jt-1} and CAR_{jt} represent the total amount of area that is registered for the CAR in a municipality *j* at time period *t-1* and *t*, respectively, assuming there can be a lag in how the CAR affects land use; X_{jt} includes prices, P_{jt}, biophysical, B_{jt}, and socioeconomic variables, Z_{jt}, that are exogenous or endogenous in a municipality *j* at time period *t*; γ_t is time fixed effects; and ε_{jt} is an error term. We test the hypothesis of no second order serial autocorrelation to check whether the Arellano Bond model assumptions are satisfied.

The first-differencing nature of the above model controls for all municipality fixed effects that do not vary over time. This includes many biophysical variables such as temperature, soil quality, slope and elevation (Table 1) that do not vary in the short term as well as distance variables such as distance to cities and major markets that also affect production decisions. We additionally control for the annual precipitation that affects production and therefore people's land use decisions. Socioeconomic variables, Z_{jt}, include endogenous institutional factors such as fine intensity, credit density, and protected area variables that affect farmers' land use decisions. We also include a measure of municipal GDP per capita as an endogenous variable to control for overall municipal economic activity. Population density indicates how urban a municipality is and reflects the labor availability for production and land use pressures (Geist and Lambin 2002; Hargrave and Kis-Katos 2013). Other institutional and economic factors that we control for include the percentage of people who, according to the Forest Code, have more than the legally-required amount of native vegetation (compliance rate) and the average CAR property size, which we treat as endogenous control variables. We always treat the year effects, population density, and the total average precipitation as exogenous control variables. All price variables are treated as endogenous when running the regression using the crop area as a dependent variables and only cattle price is treated as endogenous when running the regression using the pasture area as a dependent variable.

Selection bias

Our dynamic model addresses the endogeneity issues of CAR area and other covariates. However, we further check the robustness of the results by explicitly modelling for the "selection bias" that arises because farmers' decisions to register for the CAR is likely not random but may be influenced by a variety of factors. For instance small-holder farmers might be less likely to register for CAR due to financial barriers in the registration process (Jung et al. 2017), while farmers involved in specific activities (i.e. cattle ranchers) might be particularly incentivized to register as it could affect their market access (Gibbs et al 2015). Moreover, it is likely that differences between high- and low-CAR registered municipalities increase the likelihood of observed/unobserved pre-CAR differences which may interact differently with the outcome variable, and thus mask themselves as CAR-specific effects. For instance, municipalities with large areas eligible for the CAR likely also have more areas available for crop or livestock expansion. Likewise, municipalities with more pasture area may have higher pasture expansion rates, though conversely, municipalities with large tracts of pasture pre-CAR (2006) might currently inhabit more degraded pasture areas and are abandoning pasture area at a higher rate.

Following Fong et al. (2017) we use the CBGPS method to create inverse propensity score weights which directly minimize the correlation between treatment and covariates when included in regression models, in effect mimicking the experimental condition of randomness which allows for causal inferences to be made. The CBGPS method builds on propensity score methods for binary treatments but is shown to be more robust to model misspecifications, and as a *generalized propensity score* (Hirano and Imbens 2004; Imai and van Dyk 2004) has the added benefit of being applicable to a continuous treatment variable such as our CAR variable (Fong et al. 2017). We use the CBGPS method's parametric approach to estimate the generalized propensity score as it generated weights with acceptable correlation levels despite being far less computationally intensive than the non-parametric approach. First, the CAR treatment (CAR_j^*) and pre-treatment covariates ($X_{j_{pre}}^*$) are centered and orthogonalized to have zero mean and unit variance and pass the assumption of a standard normal distribution necessary for the parametric approach. The weights are then given by

$$\frac{f\left(CAR_j^*\right)}{f_{\hat{\theta}}(CAR_j^*|X_{j_{pre}}^*)}$$

, where the numerator is a stabilizing factor (Robins et al. 2000) and $\hat{\theta}$ is obtained by numerically solving the moment conditions as specified in Fong et al. (2017).

As pre-treatment covariates ($X_{j_{pre}}^*$) we focus on variables which likely influence both CAR registration and crop and pasture area (see section 4.4. and beginning of section 4.5). We use values from 2006 when available (see Table 1 column (2)) because of the following two reasons: 1) CAR registration was still low at that time and it is necessary to ensure that none of the covariates were affected by the CAR registration, i.e., minimizing the endogeneity problem and 2) the Agricultural Census 2006 (IBGE, 2006) offers a high quality dataset with important pre-treatment covariates that might have influenced CAR registration. We use total crop and pasture area in each municipality, and create the average municipal farm size from the Agricultural Census 2006[12]. The pre-treatment covariates ($X_{j_{pre}}^*$) also include other variables using the same sources used for the main equation (2) described in section 4.3, which include crop and cattle prices, fine intensity, credit density, GDP per capita and population density in 2006.

In addition, we use average long-term (>25 years between 1950-1990) municipal rainfall and temperature calculated by Alvares et al. (2013) to capture general biophysical conditions in municipalities (as opposed to yearly variation between 2011-2015 used in the main regression). We also add other time-invariant biophysical variables that are included as municipality fixed effects in the main regression: slope and elevation based on a global digital elevation model (Aster GDEM 2011), as well as a municipal remoteness variable, i.e. a measure of the minimum travel time (in minutes) from the centroid of each municipality to a city with minimum 50,000 inhabitants (in year 2010 (IBGE 2015), based on an algorithm from the Joint Research Centre of the European Commission (2014), which incorporates information on land cover (European Space Agency 2014) and transportation routes (FGM, 2013)[13]. Lastly, we consider

[12] Due to the data issues in MapBiomas in earlier years (see discussions in the Appendix) we refrain from using crop and pasture area from this source.

[13] We initially calculated four different travel times (to cities of different sizes - additionally 10,000 and 150,000 inhabitants and state capitals). However, we only consider the latter given their high correlation to travel times to

the total area in each municipality eligible for the CAR. We do not consider the area under protection because this area is already captured in the CAR eligible area variable. For the final CBGPS weights we exclude long-term average temperature due to its high correlation to average elevation (r = -0.93) and total municipal area due to its high correlation to the other spatial covariates, e.g. CAR eligible area (r = 0.94).

We create one set of weights for each model sample, i.e. the full sample and the five reduced samples used in our robustness check (section 5). To arrive at acceptable weights for each sample we loop through a series of covariate combinations and create weights based on each combination, from which we select the ones that obtain the lowest weighted correlations across all covariates discussed above. This step results in six sets of weights all of which achieve great reductions in CAR-covariate correlations (see Table A2 and Figure 2). We run our main model with and without the weights to further assess the influence of non-random nature of CAR registration on our results.

Heterogeneous impacts and mechanisms

Following the conceptual framework, we first test potential heterogeneous impacts caused by the size of CAR registered properties in each municipality by including interaction terms in our dynamic panel model. We define 'municipalities with a majority of small-scale properties' as those with an average property size of CAR registered units below 300 ha in 2011 (baseline year), which corresponds to the threshold that the Brazilian government uses to divide small and medium or large scale farmers.

Second, we explore whether CAR registration has caused any changes in the total credit amount granted in municipality *j* in time period *t*, $Credit_{jt}$. This enables us to test whether credit can have served as a mechanism that mediates the relationship between the CAR and land use. We estimate the following equation:

(2) $$Credit_{jt} = \theta_j + CAR_{jt} + X_{jt}\beta + \gamma_t + \varepsilon_{jt}$$

where θ_j is municipality fixed effects that control for initial conditions for each municipality; X_{jt} includes the same socioeconomic and biophysical variables that vary over time and that are used in the main land use equations; γ_t controls for time-fixed effects.

We also estimate the same equation by interacting the CAR area variable, CAR_{jt}, with indicators of whether a municipality is pasture dominant and whether it has a majority of small-scale properties or not. We follow Assunção et al. (2016) by defining pasture dominant municipalities as those where the credit

50,000 inhabitant cities (r = 0.81 – 0.93) and the link between land use and remoteness to medium-sized cities (Carranza et al., 2014).

used for livestock production is higher than for crop production in the baseline year 2011, resulting in 84 out of 142 and 88 out of 140 pasture dominant municipalities in PA and MT, respectively. Lastly, we subset municipalities into two different categories by using the Forest Code compliance rate and run the above credit equation. To assess Forest Code compliance rates, we estimate the proportion of CAR properties above the legal limit for natural vegetation cover per property, e.g., 80% for Amazon and 35% for Cerrado municipalities (see section 4.2). We define "high compliance municipalities" as 25% of total observations (4^{th} quartile) with the highest compliance rate in 2011 and the rest as "low compliance municipalities".

5. Robustness check

Exclusion of observations with poor data quality

We address the potential bias that can arise from the measurement error of one of our dependent variables, pasture area (Figure A1). We do so by re-running all pasture models using only a subset of the municipalities with better data quality. Specifically, the subset of observations ranges from 632 to 1,127 as these include municipalities with maximum 20%, 30%, 40%, and 50% of their total farm area classified as "crop or pasture" across estimation years (current and two year lagged values)[14].

Our underlying assumption is that the factors contributing to changes in crop or pasture area are not correlated with factors affecting CAR registration rates. Therefore, consistent results after the exclusion of observations with bad data quality will indicate that our main results when using all observations are not caused by measurement errors driven by the omission of the crop or pasture area variable.

6. Results

Reduced selection bias

Without covariate adjustment we find evidence of selection bias in our sample. CAR registration appears particularly dependent on area eligible for the CAR and on pasture area (Figure 2). The dependence of CAR registration on eligible land is expected, while the high correlation between the CAR and pasture area is

[14] We also run models with maximum 10% of farm area classified as "crop or pasture". However, we do not report the results here because we find that the models perform poorly in terms of statistical tests for appropriateness of the model resulting from a very low sample size (n=291) and because of the difficulty in achieving acceptable CBGPS weights with low correlations between CAR area and covariates.

likely driven by the added incentive to register for the CAR amongst cattle ranchers in our study area (Gibbs et al. 2015), though we note that soy farmers are also now required to have CAR. When applying the CBGPS weighs, however, selection bias is greatly reduced. All but one covariate now have a CAR-covariate correlation below 0.2 in the full sample (Figure 2), while in the reduced robustness samples the average CAR-covariate correlations range only 0.084 to 0.129 (Table A2 in the *Appendix*).

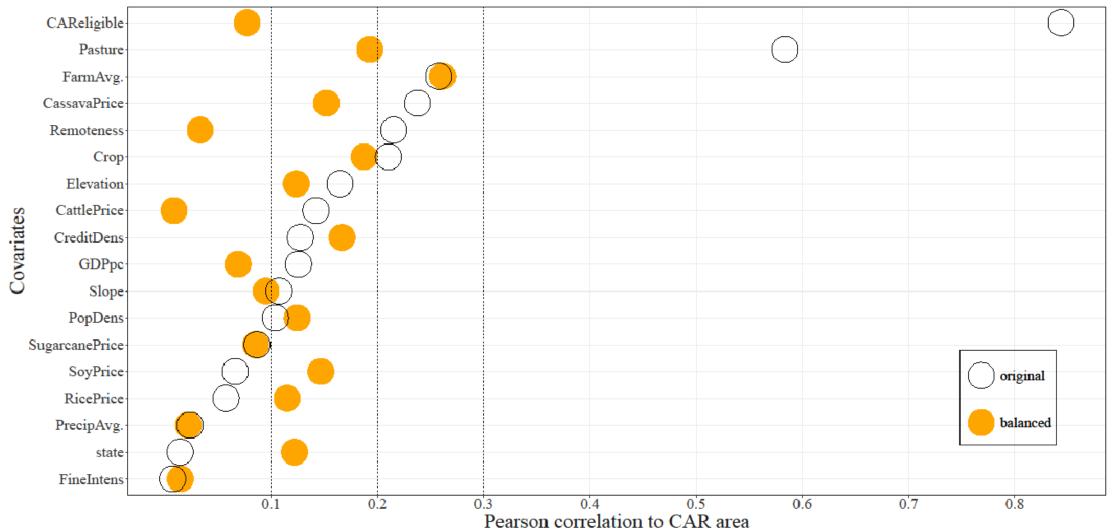

Figure 2. Adjustment of pre-CAR covariates in the full sample (obs = 1414), showing a clear reduction in correlation between CAR and covariates originally (white circles) and CBGPS adjusted covariates (orange circles)

Impacts of the CAR on crop and pasture area

In this section, we present results from the dynamic panel model investigating how CAR registration has affected changes in crop and pasture area. Table 2 shows the impacts of CAR on crop area, which is the dependent variable in all specifications (1)-(6). The specifications include three sets of panels that show results from models with 1) total area registered for the CAR, 2) an interaction term between CAR registered area and state level (PA as baseline), and 3) an interaction term between CAR registered area and average size of CAR registered properties (avg. CAR properties >300 ha as baseline, Small = avg. CAR properties <300 ha). We find that the coefficients of the lagged dependent variable are all positive and significant with values ranging from 0.63 to 0.73, validating our conceptual framework and empirical specification that past realizations of crop area has significant impacts on current crop area. The null hypothesis of no 2nd order serial correlation is not rejected and Hansen test of overidentifying restrictions does not reject the validity of instruments, also validating our dynamic model. Our main independent variable of interest, CAR area, and its lagged values do not appear to be significantly explaining the changes in crop area in any specifications with or without weights. This pattern is the same at 5% level of significance even if we consider different impacts by state and size of the CAR registered properties.

Table 2. The impacts of the CAR, without and with covariate balancing weights, on total crop area overall (1-2), by state (3-4) and CAR property size (5-6)

	Dependent variable: crop area					
	(1)	(2)	(3)	(4)	(5)	(6)
Crop area$_{t-1}$	0.627***	0.725***	0.672***	0.825***	0.630***	0.731***
	(0.111)	(0.136)	(0.120)	(0.165)	(0.110)	(0.145)
CAR	0.0154	0.0139	-0.0232	-0.0377	0.0182	0.0174
	(0.0142)	(0.0125)	(0.0403)	(0.0627)	(0.0135)	(0.0136)
CAR$_{t-1}$	0.00824	-0.0411	0.0162	-0.0231	0.00132	-0.0582
	(0.0120)	(0.0496)	(0.0223)	(0.0491)	(0.0137)	(0.0654)
CAR × Mato			0.0447	0.0502		
Grosso			(0.0409)	(0.0649)		
CAR$_{t-1}$ × Mato			-0.0238	-0.194*		
Grosso			(0.0502)	(0.0995)		
CAR × Small					-0.000968	-0.0252
					(0.0285)	(0.0441)
CAR$_{t-1}$ × Small					-0.0284	0.0386
					(0.0802)	(0.108)
Weight	No	Yes	No	Yes	No	Yes
A-B test (p)	0.854	0.756	0.979	0.673	0.893	0.752
Hansen test (p)	0.802	0.519	0.737	0.175	0.588	0.234
N	848	848	848	848	848	848

Notes: Control variables include population density, precipitation, and year-fixed effects that are exogenous and an index of prices of rice, sugarcane, cassava, soy, and cattle, area under protected area, GDP per capita, credit and fine density, average property size, and CAR compliance rate that are treated as being endogenous. ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. A-B test means Arellano-Bond test for AR (2).

We also test whether the impact of the CAR is different among different land uses and investigate the changes in land use for pasture. Table 3 shows the results from the same model specifications as table 2 but here using pasture area as the dependent variable. The appropriateness of the dynamic model where previous year's pasture area is a significant determinant of current year's pasture area is also confirmed here. The coefficients on the CAR variable without state or property size interactions suggest that the amount of land used for pasture decreases as CAR area increases (columns (1)-(2)). The results are consistent whether the weight is used or not. The significance disappears when we include state interaction effects with the CAR variable both with and without using the weight (columns (3)-(4)), though we note that the interaction itself does not appear significant. In addition, since the Hansen test of overidentifying restrictions for these two estimates rejects the validity of instruments at 10% level of significance, we rely more on the estimates of (1), (2), and (6). The same consistent patterns of negative and significant impacts of the CAR on annual changes in pasture area is present when the CAR property size interaction terms is added (column (6)) though the interaction term is not statistically significant.

Table 3. The impacts of the CAR, without and with covariate balancing weights, on pasture area overall (1-2), by state (3-4) and CAR property size (5-6)

	Dependent variable: pasture area					
	(1)	(2)	(3)	(4)	(5)	(6)
Pasture area$_{t-1}$	0.560***	0.450***	0.439***	0.402***	0.476***	0.445***
	(0.0546)	(0.0578)	(0.0937)	(0.0642)	(0.118)	(0.0762)
CAR	-0.67***	-0.644***	-0.582	-0.189	-0.683***	-0.568***
(1000 ha)	(0.15)	(0.212)	(0.894)	(0.935)	(0.211)	(0.208)
CAR$_{t-1}$	0.489	-0.211	0.912	0.113	0.0584	-0.196
(1000 ha)	(0.399)	(0.431)	(0.748)	(0.657)	(0.672)	(0.745)
CAR (1000 ha) ×			0.186	-0.402		
Mato Grosso			(0.834)	(0.909)		
CAR$_{t-1}$ (1000 ha) ×			-1.96	-0.411		
Mato Grosso			(1.32)	(0.875)		
CAR × Small					2.62	2.63
(1000 ha)					(2.78)	(2.78)
CAR$_{t-1}$ (1000 ha) ×					2.55	-0.71
Small					(3.01)	(2.94)
Weight	No	Yes	No	Yes	No	Yes
A-B test (p)	0.116	0.321	0.445	0.379	0.421	0.230
Hansen test (p)	0.167	0.220	0.025	0.093	0.011	0.177
N	848	848	848	848	848	848

Notes: Control variables include population density, precipitation, prices of rice, sugarcane, cassava, and soy, and year-fixed effects that are exogenous and price of cattle, area under protected area, GDP percapita, credit and fine density, average property size, and CAR compliance rate that are treated as being endogenous. ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. A-B test means Arellano-Bond test for AR (2).

Due to the problems with the aggregated pasture and crop area in the early years of the Mapbiomas dataset, Table 4 shows results from the robustness models restricting observations to only those that have the ambiguous crop or pasture area below 50% to 20% of total agricultural area. Overall, the estimated coefficients show consistent patterns of negative and significant impacts of the CAR on change in pasture area although column (5) with weight and valid test results at 10% level of significance show insignificant impacts[15]. Taken together, it suggests that the negative and significant impacts found are not driven by the municipalities with a high proportion of crop or pasture. In fact, if that was the case one would likely find that CAR registration increases pasture area given that most of the crop or pasture area in earlier years turns into pasture area in later years.

Table 4. The impacts of the CAR, without (1-4) and with (5-8) covariate balancing weights, on pasture area by varying the degree of the percentage of agriculture or pasture area over the total agricultural area

	Dependent variable: pasture area							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	50%	40%	30%	20%	50%	40%	30%	20%
Pasture area$_{t-1}$	0.54***	0.53***	0.49***	0.43***	0.51***	0.52***	0.53***	0.39***
	(0.05)	(0.05)	(0.06)	(0.08)	(0.06)	(0.05)	(0.06)	(0.07)
CAR (1000 ha)	-0.58***	-0.60***	-0.50***	-0.44**	-0.27	-0.49***	-0.21	-0.30**
	(0.14)	(0.13)	(0.14)	(0.19)	(0.17)	(0.16)	(0.14)	(0.14)
CAR$_{t-1}$ (1000 ha)	0.54	0.58	0.56	-0.13	-0.56	-0.35	-0.14	-0.07
	(0.43)	(0.44)	(0.38)	(0.33)	(0.48)	(0.50)	(0.38)	(0.48)
Weight	No	No	No	No	Yes	Yes	Yes	Yes
A-B test (p)	0.084	0.126	0.643	0.154	0.260	0.121	0.360	0.061
Hansen test (p)	0.145	0.134	0.093	0.0342	0.247	0.160	0.081	0.059
N	734	686	600	408	734	686	600	408

Notes: Control variables include population density, precipitation, index of prices of rice, sugarcane, cassava, and soy, and year-fixed effects that are exogenous and price of cattle, area under protected area, GDP per capita, credit and fine density, average property size, and CAR compliance rate that are treated as being endogenous. ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. A-B test means Arellano-Bond test for AR (2).

The significant negative impacts of the CAR on annual change in pasture area in Table 3-4 indicate that expansion of pasture area slows down as CAR area increases. One possible reason is that the CAR

[15] We find that the CAR variable at 50% threshold becomes significant when we decrease the number of instruments by restricting the use of lagged variables as instruments for difference equations.

encourages a shift in agricultural production from pasture to crop production, however, we do not find support for this since our previous results showed no significant increase in crop area. As the effect of the CAR is consistently negative with/without covariate balancing weights, it is also unlikely that these estimates suffer from selection bias. In the following, we probe deeper into the plausible explanations for the negative impacts of the CAR by investigating 1) heterogeneous impacts of CAR registration on pasture area by property size and 2) how the CAR might have changed access to credit and how that in turns affects land use decisions.

Heterogeneous impacts due to the size of CAR registered properties and credit use

Table 5 shows the result from having an interaction term between CAR area and average CAR property size, i.e. small ≤ 300 ha vs medium and large ≥ 300 ha. While we find evidence of negative impacts of CAR registration on pasture area, which is shown by negative and significant coefficients of the CAR variable in columns (1)-(4), none of these estimates pass the Hansen test of overidentification restriction at 5% level of significance although there is no evidence of 2nd order serial correlation. When using the covariate balancing weights (columns (5)-(7)) all required tests are passed showing no evidence of 2nd order serial correlation and proving the validity of instrument. We find evidence of heterogeneous impacts showing that the CAR has had positive and significant impacts on changes in pasture area in municipalities with smaller average CAR property size (<300 ha).

Table 5. The impacts of the CAR, without (1-4) and with (5-8) covariate balancing weights, on pasture area including interactions with the average size of CAR registered properties by varying the degree of the percentage of cropped or pasture area over the total agricultural area

	Dependent variable: pasture area							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	50%	40%	30%	20%	50%	40%	30%	20%
Pasture area$_{t-1}$	0.47***	0.51***	0.52***	0.43***	0.48***	0.53***	0.62***	0.38***
	(0.11)	(0.08)	(0.07)	(0.08)	(0.08)	(0.06)	(0.08)	(0.07)
CAR (1000	-0.55**	-0.59***	-0.49***	-0.41**	-0.20	-0.39**	-0.10	-0.31
ha)	(0.219)	(0.18)	(0.14)	(0.19)	(0.15)	(0.18)	(0.20)	(0.19)
CAR$_{t-1}$	-0.441	0.0330	0.343	-0.016	-0.585	-0.120	0.493	-0.382
(1000 ha)	(0.518)	(0.537)	(0.392)	(0.524)	(0.831)	(0.664)	(0.770)	(0.587)
CAR (1000	3.45	3.17	5.40**	1.87	5.45**	6.27**	7.78**	0.55
ha) × Small	(3.23)	(3.05)	(2.19)	(2.43)	(2.52)	(2.73)	(3.71)	(1.08)

CAR_{t-1} (1000 ha) × Small	3.14 (2.27)	0.80 (2.87)	-3.99** (1.83)	-2.20 (1.54)	-2.20 (2.08)	-3.58* (2.14)	-5.22* (2.65)	0.80 (1.37)
Weight	No	No	No	No	Yes	Yes	Yes	Yes
A-B test (p)	0.466	0.293	0.977	0.106	0.210	0.154	0.505	0.108
Hansen test (p)	0.004	0.017	0.033	0.017	0.420	0.132	0.392	0.012
N	734	686	600	408	734	686	600	408

Notes: Control variables include population density, precipitation, prices of rice, sugarcane, cassava, and soy, and year-fixed effects that are exogenous and price of cattle, area under protected area, GDP per capita, credit and fine density, average property size, and CAR compliance rate that are treated as being endogenous. ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. A-B test means Arellano-Bond test for AR (2).

One of the potential mechanisms that might have caused the heterogeneous impacts on pasture area is access to credit. Small-scale properties might have obtained access to credit through CAR registration which allowed them to expand pasture area, whereas many larger properties likely had some form of credit or other resources needed to clear pasture independent of getting the CAR. Table 6 shows that the increase in area under the CAR is negatively associated with total credit value in municipalities with smaller average property size (<300 ha) compared to municipalities with medium or large sizes of registered properties (>300 ha) in crop dominant municipalities. In pasture dominant municipalities, the CAR is negatively associated with the credit value, though when the covariate balancing weights are introduced the significance goes away, which might suggest that the selection bias could have driven significant unweighted results. However, the pattern changes for pasture dominant municipalities with smaller average property sizes. In those municipalities, the increase in area under the CAR is positively associated with increased total credit value as represented by positive and significant coefficients of the three-way interaction term (*Pasture dominant × CAR × Small*) in all specifications, i.e. both with and without covariate balancing weights and with/without possibly endogenous variables.

Table 6. The impacts of the CAR, without and with covariate balancing weights, on total credit value including interactions whether average CAR property size is small or large and whether a municipality is crop or pasture dominant (1-2), also controlling for additional predictor variables (3-4)

	Dependent variable: credit value			
	(1)	(2)	(3)	(4)
CAR	178.3***	131.1***	164.9***	126.7***
	(61.61)	(46.63)	(57.33)	(38.43)
CAR × Small	-352.9***	-246.8***	-384.0***	-263.2***
	(87.48)	(54.92)	(86.22)	(50.51)
Pasture dominant × CAR	-123.3**	-67.20	-111.9**	-55.85
	(56.21)	(43.32)	(52.30)	(38.01)
Pasture dominant × CAR ×	328.0***	174.4***	359.6***	182.7***
Small	(90.61)	(60.24)	(89.37)	(58.26)
Protected area			-70387.8***	-57540.0***
			(14251.1)	(17838.6)
Fine intensity			0.0218	0.0642
			(0.0401)	(0.0548)
Compliance rate			241271.4*	280512.8*
			(130826.9)	(148171.1)
Weight	No	Yes	No	Yes
N	1415	1414	1414	1414

Notes: Other common control variables include municipality fixed effects, population density, GDP per capita, precipitation, prices of rice, sugarcane, cassava, cattle, and soy, and year-fixed effects. ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively.

This negative or insignificant impacts of the CAR on the total credit value in pasture dominant municipalities support the main result showing significant and negative impacts of the CAR on pasture area. The pasture dominant municipalities with larger average property sizes (>300 ha) might have had restricted use of credit due to the higher proportion of properties that were not in compliance with the Forest Code. This argument is supported by the evidence shown in Table 7 when the same model is estimated using only a subset of municipalities with low and high compliance rates and using weights[16]. The negative and significant coefficient of the variable *Pasture dominant × CAR* indicates that the CAR has negative

[16] The models that do not use weights show the same patterns.

impacts on credit value in municipalities with medium or large average property sizes and with lower compliance rates. The significance disappears and magnitude greatly reduces when only municipalities with high compliance rate are considered, which suggests that CAR registration does not have significant negative impacts on credit when a higher percentage of properties are in compliance with the Forest Code.

Table 7. The impacts of the CAR, without and with controlling for additional predictor variables, on total credit value including interactions with whether average CAR property size is small or large and whether a municipality is crop or pasture dominant, using observations by low (1-2) and high (3-4) compliance rate. All models use covariate balancing weights.

	Dependent variable: credit value			
	Low compliance (Low 75%)		High compliance (Top 25%)	
	(1)	(2)	(3)	(4)
CAR	223.4***	208.4***	30.34	41.57
	(54.42)	(54.49)	(34.17)	(34.29)
CAR × Small	-336.6***	-345.9***	-850.0***	-1190.3*
	(63.70)	(63.56)	(295.3)	(609.2)
Pasture dominant × CAR	-135.9**	-124.2**	-13.36	-11.46
	(53.99)	(53.64)	(38.11)	(39.23)
Pasture dominant × CAR ×	248.7***	262.4***	880.7***	1221.8**
Small	(67.52)	(69.28)	(300.5)	(593.8)
Protected area		-34908.6**		
		(15825.7)		
Fine intensity		-0.00785		0.329***
		(0.0247)		(0.0947)
Compliance rate		-65935.4		169066.2
		(250141.5)		(110025.4)
Weight	Yes	Yes	Yes	Yes
N	1065	1065	349	349

Notes: Other common control variables include municipality fixed effects, population density, GDP per capita, precipitation, prices of rice, sugarcane, cassava, cattle, and soy, and year-fixed effects. ***, **, and * indicate 1%, 5%, and 10% level of significance, respectively.

It is also notable that the magnitudes of coefficients of *Pasture dominant × CAR × Small* for high compliance municipalities in Table 7 are more than threefold of those for low compliance municipalities.

This further supports the evidence from Table 6 that the increase in area under the CAR might have driven increases in total credit value in municipalities that are pasture dominant and have smaller average size of CAR registered properties. Though it does not test it explicitly, our results suggest that credit access could be mediated by the level of compliance with the Forest Code. The higher credit value associated with more CAR registered area in municipalities that are pasture dominant but have small average size of CAR registered properties could be the mechanism through which an increased CAR registered area causes more pasture area.

7. Discussion

This paper has sought to contribute to the literature on relations between the national Rural Environmental Registry in Brazil and farmers' land use strategies. Although this theme has found some recent attention (Azevedo et al 2017; Kröger 2016; Alix-Garcia et al. 2018), existing work has largely focused on whether or not reduced deforestation rates were achieved, thereby creating a blind spot with respect to other types of land use than forest as well as the mechanisms underlying farmers' land use decisions. Our paper is a step forward as it explores the mechanisms through which increasing CAR registration rates affect cropped area and pasture area at the municipality level.

Our empirical results show significant but heterogeneous impacts of the CAR on pasture area and support our expectation that the CAR has changed institutional and market conditions in Brazil and affected how farmers use their land. More specifically, we find that the CAR registration has slowed expansion of pasture area for medium- and large-scale farmers while increasing pasture expansion for small-scale farmers. These results are consistent across models with and without covariate balancing weights. In all cases where the weighted and unweighted models vary, they do so only in terms of magnitude of impact and in only a handful of cases to the point where the influence of the CAR disappeared.

We find that municipalities dominated by small-scale properties and crop-producing farmers use less rural credit but that rural credit is strongly associated with higher rates of CAR registration in pasture dominant municipalities where the majority are small properties and, even more so, where levels of compliance with the Forest Code are high. Our finding that CAR registration caused pasture expansion on small properties suggests that small properties could be registering in the CAR to access credit. The promise of increased market access by registering for the CAR might have been particularly important for small-scale farmers because small-scale farmers are generally more credit-constrained and tend to have fewer market options (Deininger and Feder 2001; de Castro and Teixeira 2012). As such the increase in pasture area for small-scale farmers as CAR registration rates increase may partly be driven by the rise in profitability enjoyed by ranchers who, as a result of registering for the CAR, gain access to new markets.

Indeed, as the CAR has become the primary way to demonstrate environmental compliance, small-scale farmers getting the CAR may be embarking on a process of entering the market more formally (Rasmussen et al. 2017). Thus, the CAR, with its fairly low barriers to participation, may be playing an unexpected role of supporting the formalization of small-scale production and, thereby, accelerating pasture expansion. Since the requirements of proof of legal compliance are sometimes not as restrictive for small-scale farmers as they are for medium- and large-scale, the CAR might have also driven expansion of the pasture area in municipalities with small-scale properties.

The finding that medium- and large-scale cattle ranchers reduce the expansion of pasture area as the CAR area increases may also reflect the impacts of zero-deforestation agreements (de Waroux et al. 2017). Beginning in 2009, efforts to remove deforestation from cattle supply chains have incentivized CAR registration and major cattle buyers began to use CAR boundaries to monitor for deforestation. Under these policies, properties with deforestation are excluded from delivering cattle to the slaughterhouses in addition to the limitations on obtaining subsidized credit. As a result, ranchers may have changed their farming practices by shifting production from livestock to crops (though we find no evidence of this) or by intensifying production in order to comply with these policies without additional deforestation (Gibbs et al. 2015). In particular, the heterogeneous impacts showing negative and significant impacts of the CAR area on credit value for medium- and large-scale farmers in pasture dominant municipalities, which are only present when using municipalities with low compliance rates, supports the idea of the government's credit policy being the major driver of the decrease in the expansion of the pasture area. Although we do not directly test it, this impact of the CAR through credit access for larger-scale ranchers could have been magnified by the zero-deforestation agreement in the cattle sector. An alternative explanation for the observed decrease in the expansion of pasture area in municipalities with primarily medium or large-scale properties might be that farmers have increased productivity on parts of their land allowing for some areas to be abandoned. Reasons for this might be linked to the CAR and the need to restore natural vegetation for Forest Code compliance, or to non-CAR related issues, such as a move toward more intensified production, which could involve the abandonment of less productive areas.

There are two potential explanations of why we do not see any significant impacts of the CAR on crop area. First, it is possible that CAR registration did not change farmers' land use decisions for crop production because of little or insufficient enforcement of environmental regulations using the CAR database and the absence in crop systems/markets of the other factors that led to changes in pasture area. If so, farmers could continue with what they were doing on their land even after CAR registration and regardless of the properties' compliance with the Forest Code. Alternatively, it is plausible that the impacts of the CAR might differ by the crop type such that they are buried in the aggregate estimation of impacts. For example, the CAR might have changed the area under soybean production as the soy moratorium emerged in 2008 and imposed binding constraints on farmers' land use in the same way that the zero-deforestation cattle agreements did. Second, farmers might have had sufficient land cleared for crop production (Alix-Garcia et al. 2018). In other words, the total amount of cultivated land might not have changed significantly. In fact, cattle rearing in the north of Brazil is generally low intensity and thus holds a large capacity for productivity increases particularly compared to the already highly intensive soybean production system (Strassburg et al. 2014). Therefore, a marginal increase or decrease in crop area might not be as significant as that of pasture area following CAR registration.

Our findings complement and advance other studies by 1) providing robust empirical evidence on heterogeneous impacts of the CAR on land use, 2) investigating potential mechanisms through monitoring and credit using both theoretical and empirical models, and 3) estimating the impacts at the municipality level, which is advantageous in the attempt to tease out both direct and indirect impacts. Our study advances contributions made by others including L'Roe et al. (2016), showing heterogeneous impacts of the CAR and its potential to formalize markets. The formalization of markets was evidenced by the small-scale farmers' increased use of credit, being highly associated with the greater CAR area. This supports the evidence suggested by Rasmussen et al. (2017) that small-scale farmers might be incentivized to clear more land for production when they are granted access to credit through the CAR registration. Our results also suggest that the use of CAR data to monitor deforestation by private initiatives in the cattle sector might have decreased pasture expansion. This corroborates Gibbs et al. (2015) and Alix-Garcia and Gibbs (2017) showing that the zero cattle agreement decreased deforestation although leakages were found through laundering.

8. Conclusion

There is a growing interest among scholars and practitioners to investigate environmental outcomes of the CAR. While previous efforts have been focused on deforestation, our study is the first to estimate the impacts of the CAR on land use: crop and pasture. Focusing on two states in Brazil, we find evidence that the CAR has significantly influenced land use. That is, the CAR slowed pasture expansion on large-scale farms, whereas it led to more expansion on small-scale farms. Our results suggest that the access to credit lines and markets which farmers gain through the CAR might have contributed to these heterogeneous impacts. Taken together, these results have implications for conservation and development policies as they outline how policies and private initiatives that control credit access might undermine the core environmental objectives of the CAR in areas dominated by small-scale farms.

9. References

Alix-Garcia, J. and Gibbs, H.K. 2017. Forest conservation effects of Brazil's zero deforestation cattle agreements undermined by leakage. *Global Environmental Change*, 47: 201-217.

Alix-Garcia, J., Rausch, L.L., L'Roe, J., Gibbs, H.K. and Munger, J. 2018. Avoided deforestation linked to environmental registration of properties in the Brazilian Amazon. *Conservation Letters*, *11*(3):p.e12414.

Alvares, C.A., Stape, J.L., Sentelhas, P.C., De Moraes Gonçalves, J.L., and Sparovek, G. 2013. Köppen's climate classification map for Brazil. *Meteorologische Zeitschrift*, 22(6): 711-728.

Arellano, M. and Bond, S. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, 58(2): 277-297.

Assunção, J., and Gandour, C. 2016. Does Credit Affect Deforestation? Evidence from a Rural Credit Policy in the Brazilian Amazon. Climate Policy Initiative, Rio De Jaineiro, Brazil.

Assunção, J., Gandour, C. Pessoa, P., and Rocha, R. 2017a. Property-level assessment of change in forest clearing patterns: The need for tailoring policy in the Amazon. *Land Use Policy*, 66:18-27.

Assunção, J., Gandour, C., and Rocha, R. 2017b. DETERring deforestation in the Amazon: Environmental monitoring and law enforcement. Working Paper, Climate Policy Initiative. Rio de Janeiro.

Aster GDEM. 2011. ASTER GDEM. Retrieved October 9, 2015, from http://gdem.ersdac.jspacesystems.or.jp/

Azevedo, A.A., Rajão, R., Costa, M.A., Stabile, M.C., Macedo, M.N., dos Reis, T.N., Alencar, A., Soares-Filho, B.S. and Pacheco, R. 2017. Limits of Brazil's Forest Code as a means to end illegal deforestation. *Proceedings of the National Academy of Sciences*, 114(29): 7653-7658.

Banco Central do Brasil. 2017. Crèdito Rural. Retrieved August 31, 2017, from http://www.bcb.gov.br/pt-br/#!/n/credrural

Börner, J., Marinho, E. and Wunder, S. 2015. Mixing carrots and sticks to conserve forests in the Brazilian Amazon: a spatial probabilistic modeling approach. *PloS one*, 10(2):0116846.

Carranza, T., Balmford, A., Kapos, V., & Manica, A. 2014. Protected area effectiveness in reducing conversion in a rapidly vanishing ecosystem: The Brazilian Cerrado. *Conservation Letters*, 7(3): 216-223.

da Silva, J.M.C., Prasad, S. and Diniz-Filho, J.A.F., 2017. The impact of deforestation, urbanization, public investments, and agriculture on human welfare in the Brazilian Amazonia. *Land Use Policy*, 65:135-142.

de Castro, E.R., and E.C. Teixeira. 2012. Rural credit and agricultural supply in Brazil. *Agricultural Econonomics*, 43(3): 293-302.

de Freitas, F.L.M., Sparovek, G., Mörtberg, U., Silveira, S., Klug, I. and Berndes, G. 2017. Offsetting legal deficits of native vegetation among Brazilian landholders: Effects on nature protection and socioeconomic development. *Land Use Policy*, 68:189-199.

de Waroux, Y.L.P., Garrett, R.D., Graesser, J., Nolte, C., White, C., and Lambin, E.F. 2017. The restructuring of South American soy and beef production and trade under changing environmental regulations. *World Development*.

Deininger, K. and Feder, G. 2001. Land institutions and land markets. In: Gardiner, B., Rausser, G. (Eds), Handbook of Agricultural Economics. Elsevier, Amsterdam, pp. 288-331.

De Sá, S.A., Palmer, C. and Di Falco, S., 2013. Dynamics of indirect land-use change: empirical evidence from Brazil. *Journal of Environmental Economics and Management*, 65(3): 377-393.

Fitz, D. 2018. Evaluating the impact of market-assisted land reform in Brazil. *World Development*, 103: 255-267.

FUNAI. 2017. Shapefiles of Indigenous Territories by Fundação Nacional do Índio. Available at: http://www.funai.gov.br/index.php/quem-somos

Gasparri, N.I., Kuemmerle, T., Meyfroidt, P., Waroux, Y. and Kreft, H. 2016. The emerging soybean production frontier in Southern Africa: Conservation challenges and the role of south-south telecouplings. *Conservation Letters*, 9(1): 21-31.

Geist, H. J. and Lambin, E. F. 2002. Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *BioScience*, *52*(2): 143-150.

Gibbs, H. K., J. Munger, J. L'Roe, P. Barreto, R. Pereira, M. Christie, T. Amaral, and N.F. Walker. 2015. Did Ranchers and Slaughterhouses Respond to Zero-Deforestation Agreements in the Brazilian Amazon? *Conservation Letters* 9(1): 32-42.

Hargrave, J., and Kis-Katos, K. 2013. Economic Causes of Deforestation in the Brazilian Amazon: A Panel Data Analysis for the 2000s. *Environmental and Resource Economics*, 54(4): 471-494.

Hirano, K., and Imbens, G. W. 2004. The Propensity Score with Continuous Treatments. In Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives: An Essential Journey with Donald Rubin's Statistical Family, Chap. 7. Wiley.

IBAMA. 2017. Autuações e embargos. Retrieved May 31, 2018, from http://www.ibama.gov.br/consultas/autuacoes-e-embargos

IBGE. 2006. Censo Agropecuário (Agricultural census). Retrieved November 25, 2014, from http://www.ibge.gov.br/english/estatistica/economia/agropecuaria/censoagro/2006_segunda_apuracao/default_tab_pdf.shtm

IBGE. 2015. SIDRA: Banco de dados agregados. Retrieved March 11, 2015, from http://www.sidra.ibge.gov.br/

IBGE. 2016. Produção Agrícola Municipal. Retrieved May 1, 2016, from http://www.sidra.ibge.gov.br/bda/pesquisas/pam/

ICMBio. 2016. Institute for Biodiversity Conservation. Available at: http://www.icmbio.gov.br/portal/

Imai, K. and van Dyk, D. A. 2004. Causal Inference with General Treatment Regimes: Generalizing the Propensity Score. *Journal of the American Statistical Association* 99(467): 854-866.

INPE. 2014. TerraClass. Retrieved August 25, 2018, from http://www.inpe.br/cra/projetos_pesquisas/dados_terraclass.php

Jung, S., Rasmussen, L.V., Watkins, C., Newton, P. and Agrawal, A., 2017. Brazil's national environmental registry of rural properties: implications for livelihoods. *Ecological economics*, 136: 53-61.

Kröger, M., 2017. Inter-sectoral determinants of forest policy: the power of deforesting actors in post-2012 Brazil. *Forest Policy and Economics*, 77: 24-32.

Latawiec, A.E., Strassburg, B.B., Silva, D., Alves-Pinto, H.N., Feltran-Barbieri, R., Castro, A., Iribarrem, A., Rangel, M.C., Kalif, K.A.B., Gardner, T. and Beduschi, F. 2017. Improving land management in Brazil: A perspective from producers. *Agriculture, ecosystems & environment,* 240: 276-286.

L'Roe, J., Rausch, L., Munger, J. and Gibbs, H.K. 2016. Mapping properties to monitor forests: Landholder response to a large environmental registration program in the Brazilian Amazon. *Land Use Policy*, 57: 193-203.

MapBiomas. 2017. Coleções MAPBIOMAS. Retrieved August 20, 2017, from http://mapbiomas.org/pages/database/mapbiomas_collection

NOAA. 2018. NOAA Climate Data Record (CDR) of Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN-CDR), Version 1 Revision 1. https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncdc:C00854

Rasmussen, L.V., Jung, S., Brites, A.D., Watkins, C., and Agrawal, A. 2017. Understanding smallholders' intended deforestation behavior in the Brazilian Cerrado following environmental registry. *Environmental Research Letters*, 12(9).

Rasmussen, L.V., Coolsaet, B., Martin, A., Mertz, O., Pascual, U., Corbera, E., Dawson, N., Fisher, J.A., Franks, P. and Ryan, C.M. 2018. Social-ecological outcomes of agricultural intensification. *Nature Sustainability*, 1(6): 275.

Rausch, L. and H. K. Gibbs. 2016. Property Arrangements and Soy Governance in the Brazilian State of Mato Grosso: Implications for Deforestation-Free Production. *Land* 5(2): 7.

Richards, P.D. and VanWey, L. 2016. Farm-scale distribution of deforestation and remaining forest cover in Mato Grosso. *Nature Climate Change*, *6*(4): 418.

Roitman, I., Vieira, L.C.G., Jacobson, T.K.B., da Cunha Bustamante, M.M., Marcondes, N.J.S., Cury, K., Estevam, L.S., da Costa Ribeiro, R.J., Ribeiro, V., Stabile, M.C. and de Miranda Filho, R.J., 2018. Rural Environmental Registry: An innovative model for land-use and environmental policies. *Land Use Policy*, 76: 95-102.

Rudorff, B.F., Adami, M., Risso, J., de Aguiar, D.A., Pires, B., Amaral, D., Fabiani, L., Cecarelli, I. 2012. Remote sensing images to detect soy plantations in the amazon biome—The soy moratorium initiative. *Sustainability*, 4(5): 1074-88.

Soares-Filho, B., Rajão, R., Macedo, M., Carneiro, A., Costa, W., Coe, M., Rodrigues, H. and Alencar, A., 2014. Cracking Brazil's forest code. *Science*, *344*(6182): 363-364.

Strassburg, B.B., Latawiec, A.E., Barioni, L.G., Nobre, C.A., Da Silva, V.P., Valentim, J.F., Vianna, M. and Assad, E.D., 2014. When enough should be enough: Improving the use of current agricultural lands could meet production demands and spare natural habitats in Brazil. *Global Environmental Change*, 28: 84-97.

Vieira, I.C., Gardner, T., Ferreira, J., Lees, A.C., Barlow, J. 2014. Challenges of governing second-growth forests: A case study from the Brazilian Amazonian State of Pará. *Forests* 5(7): 1737-1752.

Windmeijer, F. 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of econometrics*, 126(1): 25-51.

10. Appendix

Factors that drive changes in land use

We identify mechanisms through which CAR registration impacts farmers' land use decisions by using the literature and a simple household economic model. Specifically, we are interested in modelling the amount of total land used for crop and pasture production. Our empirical analyses are at the municipality level, which has the advantage of capturing aggregate impact of CAR registration on land use across municipalities. However, we start our discussion from the factors that affect individual farmer's production decisions that determine land use.

At the household level, we start from the premise that a farmer *i*'s optimal crop or pasture production area (E_{ijt}^{*}) located in a municipality *j* in period *t* is a dynamic process (de Sa´ et al. 2013). It can be defined as the sum of previous period's crop or pasture production area plus the area added or removed for crop or pasture production in year *t* such that

$$E_{ijt}^{*} = E_{ijt-1} + e_{ijt}^{*}$$

where e_{ijt} is the amount of new area for crop or pasture production ($e_{ijt} > 0$) or of previously produced area that is given up at time period *t* ($e_{ijt} < 0$). In the Brazilian context, e_{ijt} can come from either newly cleared areas or already cleared areas, e.g., secondary forest or already degraded pasture, if $e_{ijt} > 0$, which is determined by the profit-maximizing farmer *i* solving the following problem.

$$\pi_{ijt} = P_{ijt}Q_{ijt}\left(E_{ijt}, I_{ijt}\right) - C_{ijt}(W_{ijt}, E_{ijt}, I_{ijt}) \,,$$

where P_{ijt} represents output farm gate prices that farmer *i* faces, Q_{ijt} is a production function from the use of inputs including changes in land area (e_{ijt}) and other inputs (I_{ijt}), C_{ijt} is the total cost that is determined by a vector of input prices (W_{ijt}) and the level of inputs, i.e., e_{ijt}, I_{ijt}. The input levels and their prices may not be directly observable and are likely to be determined by biophysical and socioeconomic characteristics such that $I_{ijt} = I(B_{ijt}, Z_{ijt})$ and $W_{ijt} = W(B_{ijt}, Z_{ijt})$, where B_{ijt} represents biophysical characteristics that affect production such as weather and soil quality for household *i* in a municipality *j* in time period *t*; Z_{ijt} indicates other socioeconomic factors such as the availability of labor that affects individual farmer i's land use decisions at the municipality level *j* at time period *t*.

Therefore, the profit-maximizing farmer i's optimal amount of crop or pasture area in municipality *j* at time period *t*, e_{ijt}^{*}, is determined by

$$e_{ijt}^{*} = e(P_{ijt}, B_{ijt}, Z_{ijt})$$

At the municipality level with *I* number of farmers the total amount of crop or pasture area in a municipality *j* is the sum of all cropped areas or pasture areas such that

$$E_{jt}^{*} = \sum_{i=1}^{I} E_{ijt}^{*} = E_{jt-1} + \sum_{i=1}^{I} e_{ijt}^{*} = E_{jt-1} + \sum_{i=1}^{I} e(P_{ijt}, B_{ijt}, Z_{ijt})$$

Table A1. Consistency check of land use detection (total km^2 and correlation between municipalities) between MapBiomas, IBGE, and TerraClass for year 2014 for Pará (PA) and Mato Grosso (MT), values in parenthesis when MapBiomas' hybrid "crop or pasture" category is included

	Crop		Pasture	
	PA	MT	PA	MT
MapBiomas (km^2)	153	77,337	143,139	203,595
	(27,068)	(122,243)	(170,054)	(248,501)
IBGE (km^2)	12,197	136,139	NA	NA
TerraClass (km^2)	3,191	38,920	160,623	133,492
Correlation (Spearmans' rho)				
MapBiomas vs. IBGE	0.16	0.93	NA	NA
	(0.43)	(0.85)		
MapBiomas vs. TerraClass	0.26	0.61	0.98	0.61
	(0.30)	(0.48)	(0.93)	(0.54)
TerraClass vs. IBGE	0.44	0.67	NA	NA

Sources: MapBiomas v2.3 (MapBiomas, 2017), IBGE's PAM (IBGE, 2016) and TerraClass (INPE, 2014), no data available (NA) for pasture area from IBGE

Note: Table A1 shows relatively consistent detection of area under pasture by MapBiomas compared to the other available data sources. Detection of crop area by MapBiomas appear particularly poor in Para. IBGE and Terra class are more correlated, but total values also diverge here.

Table A2: Pre-CAR covariate adjustment for all reduced pasture area samples: correlations between CAR and covariates

		Original		Balanced		Difference
Threshold	N obs.	Max.	Average	Max.	Average	Percent
50%	1127	0.847	0.192	0.289	0.115	-40
40%	1054	0.846	0.193	0.315	0.084	-57
30%	926	0.84	0.183	0.329	0.097	-47
20%	632	0.82	0.192	0.375	0.108	-44
10%	291	0.814	0.199	0.479	0.129	-35

Note: Refers to maximum and average Pearson correlation between CAR and covariates in the original and balanced (Covariate Balancing Generalized Propensity Score (CBGPS) weighted) samples, and the relative change in average correlation between the two

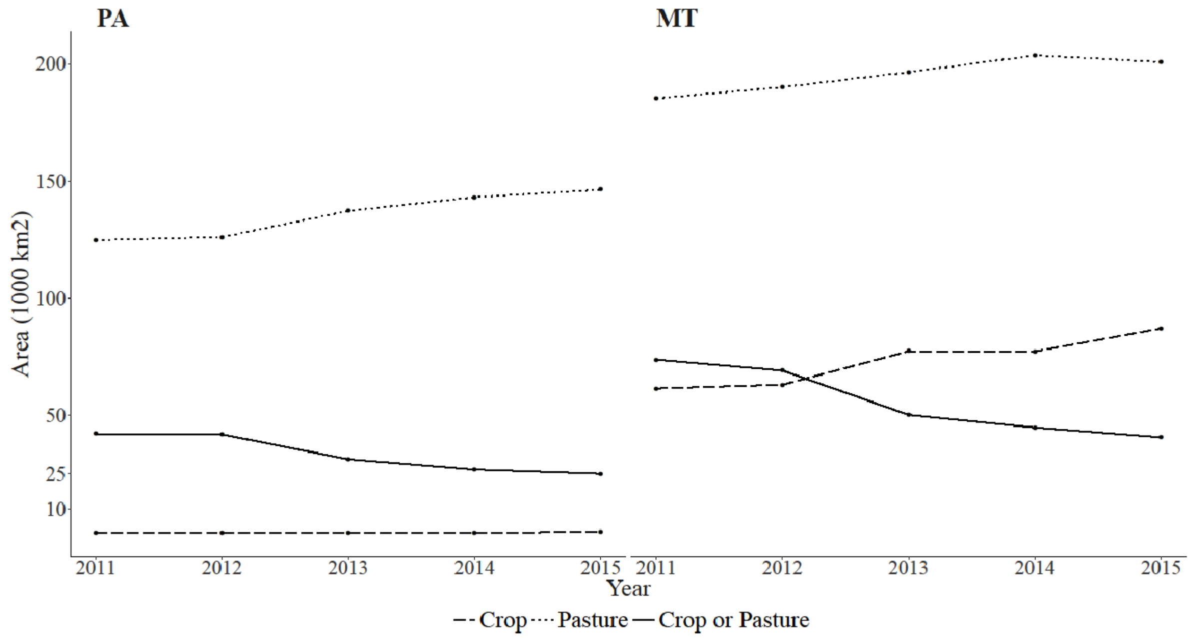

Figure A1. Farm area detection by category from MapBiomas from 2011 to 2015 for Pará (PA) and Mato Grosso (MT)

Note: Since 2011, the area classified as "crop or pasture" in MapBiomas[17] has steadily declined. Figure A1 shows a clear trend of increase in pasture area as "crop or pasture" area decreased in PA. In MT, the decrease in "crop or pasture" area is paralleled by an increase in crop area. Given the high rate of reduction in the "crop or pasture" category, the apparent shift to a pure crop or pasture area classification appears due to an improvement in the classification algorithm rather than an actual change from mixed to pure farming systems. We try to minimize the possible bias of this change on our estimation results in a robustness step detailed in section 5.1.

[17] The MapBiomas dataset refers to crop area as agricultural area, but we refer to it as crop area

Chapter 5

1. Thesis Conclusion

Global food insecurity is increasing (FAO, 2018). At the same time natural vegetation and biodiversity losses persist as a result of agriculture (Newbold et al., 2015; Tubiello et al., 2015). Currently in international discussions there is much focus on finding sustainable solutions to development. The UN's 17 Sustainable Development Goals, which was adopted by world leaders in 2015, is an example of this focus (Barbier & Burgess, 2017). Small-scale farmers are increasingly identified as vital for achieving the multiple SDGs of food security, poverty alleviation, protection of biodiversity and natural resources (Samberg et al., 2016; UNCTAD, 2015). The majority of small-scale farms live and produce in and around natural habitats and important ecosystems, and present both possible benefits and risks to these natural systems (Perfecto et al., 2009; Perfecto & Vandermeer, 2010). At the same time as being a major producer of food for human consumption (Samberg et al., 2016) small-scale farmers often experience high levels of food insecurity and poverty (UNCTAD, 2015).

This thesis took a systems approach in assessing the effect of integrated social protection and environmental programmes which target small-scale farmers on multiple sustainability outcomes. It focused on the integrated food insecurity and poverty alleviation programme Zero Hunger, and the environmental monitoring programme, the National Rural Environmental Registry (CAR), in Brazil. The thesis found that these programmes can deliver simultaneously on social and environmental outcomes, however, most often heterogeneous effects and trade-offs occur. These heterogeneities arise for three primary reasons. First, programme impacts vary across food security, multi-dimensional poverty, health and environmental outcomes, with evidence for positive, negligible and negative impacts depending on the outcome in question. Second, within a single outcome impacts vary depending on the specific programme activities, in particular whether support to small-scale farmers is given through conditional cash transfers, agricultural credit, support for agricultural market access or environmental monitoring. Third and finally, within a single outcome and specific programme activity there is considerable variation in the magnitude and even direction of impact. This variation in impact we find both spatially across Brazil and across the types of farmers that participate. These differences in impact is driven primarily by variation in local contexts and variation in characteristics of programme participants. The success of the Zero Hunger and CAR programmes, and likely the success of integrated social and environmental programmes in other developing countries, have been identified to rely on three main conditions: the presence of basic infrastructure, the presence and collaboration of institutions across sectors, and appropriate programme design and targeting to engage the poorest and most in need farmers.

Infrastructure

Hazell et al. (2007) highlight that for interventions to benefit small-scale farmer livelihoods these must "get the basics in place" (Hazell et al., 2007). Basic infrastructure is often lacking in rural areas where small-scale farmers reside, particularly service infrastructure such as schools and health centres (Barrientos, 2017). Not only do these shortcoming hinder the well-being and development of rural inhabitants, but it can also influence effectiveness of interventions aimed to improve their well-being. The large-scale study on the effect of Zero Hunger on multiple sustainability outcomes in chapter 2 found that in particular one Zero Hunger sub-programme, Bolsa Familia, has had negligible and even negative effects on multi-dimensional poverty, infant mortality and child malnutrition across rural municipalities in Brazil. A main contributing factor to these non-beneficial effects is likely the lack of presence of available basic infrastructure. This claim is supported by other Bolsa Familia studies (Piperata et al., 2016; Soares et al., 2010). For instance, to achieve (multi-dimensional) poverty alleviation in the long-term Bolsa Familia, and many conditional cash-transfer programmes in Latin America, aim to improve school attendance and health amongst children and women (Cecchini & Madriaga, 2011). To deliver on these aims they thus rely on the presence of school and health infrastructure. Yet research into budget expenditure in Brazil by Hall (2008) and Soares et al. (Soares et al., 2010) suggest that increasing investment in Bolsa Familia has come at the expense of governmental investments in basic infrastructure. In terms of getting the basics in place it is also worth noting that in several parts of Brazil poor agricultural households still lack access to basic sanitation services (Soares et al., 2016). Yet it is known that gaining access to such services has been a key driver in reducing undernutrition globally (Smith & Haddad, 2015). Lack of basic infrastructure is, however, not particular to rural areas of Brazil but is a common characteristic for many development countries (Barrientos, 2017; Devereux, 2016). Thus, when implementing social protection programmes which involve small-scale farmers it is vital that these programmes identify the presence and need of basic infrastructure, not just agricultural infrastructure but also sanitation, school and health service infrastructure. Redistributing some investment into basic infrastructure if these are missing could increase the likelihood of beneficial programme effects.

Institutional and cross sectoral collaboration

For interventions to be successful the mere presence of supporting infrastructure is rarely sufficient. The quality of the infrastructure is just as important. This is particularly the case for service or institutional infrastructure. For integrated social protection programmes that aim to achieve multiple goals, cross-sectoral institutional collaboration is also necessary to effectively deliver on programme aims (Barrientos, 2017). For instance, a lack of cross-sector monitoring capacity of the conditional aspects of Bolsa Familia in Brazil was identified as another factor limiting the beneficial effects of the programme (Araújo et al., 2018). This lack also likely explains some of the spatial heterogeneity of

Bolsa Familia effect found in chapter 2. Araújo et al., (2018) found that the the north-east of Brazil was a key exception to the monitoring challenge described above. The north-eastern region is also a region where evidence from chapter 2 suggested a significant (albeit marginal) beneficial effect of Bolsa Familia on multi-dimensional poverty alleviation across the general population. In the same region the study in chapter 2 found large positive effects of Bolsa Familia on food (protein) production.

Agricultural extension services and agricultural cooperatives are other institutions particularly relevant for small-scale farmers and can be instrumental in the success of interventions targeting small-scale farmers (Ahmed & Mesfin, 2017; Jayne et al., 2014; Mojo et al., 2015; Verhofstadt & Maertens, 2015). Jayne et al. found that small-scale farmers do not always benefit from farm focused interventions, and particularly not when there is limited support from advisory services (Jayne et al., 2014). The large-scale study of Zero Hunger in chapter 2 revealed that the largest beneficial effects of Zero Hunger overall, and PRONAF in particular, on food production and multi-dimensional poverty alleviation have occurred in the south. Here small-scale farm organization through cooperatives and access to agricultural extension offices are more common than elsewhere in the country (Helfand et al., 2015). The same beneficial trend between farm effectiveness and PRONAF in the south was found by Eusebio et al. (2016).

The Zero Hunger case study described in chapter 3 also found that the local agricultural extension office likely played an important part in farmers gaining access to and benefitting from the Zero Hunger sub-programmes PRONAF and PAA. Elsewhere in Brazil NGOs or associations often support PAA farmers in their activities (Milhorance et al., 2015). The study in chapter 3 found positive associations between PRONAF and PAA and food security measured as overall household food insecurity, change in food access and food self-sufficiency. The extension office supported farmers in the programmes inscription process and encouraged farmers to become more organized through farm cooperatives and associations. The extension office also encouraged small-scale farmers to produce more environmentally friendly, however the study found no consistent associations between PRONAF and PAA participation and use of agro-chemicals. Oppositely, lack of local institutional support and lack of sectoral collaboration was found to be a major challenge to the implementation and success of PAA based interventions in Mozambique (Milhorance et al., 2015).

Cross-sectoral collaboration is particularly important if interventions are to deliver on both societal and environmental outcomes (Sayer et al., 2013). The main ministries involved in the Zero Hunger programme are the Ministry of Social Development and the Fight against Hunger, the Ministry of Health and the Ministry of Agrarian Development (Silva, Grossi, & França, 2011). Noticeably there are no direct programme links to the Ministry of Environment despite its main target group, i.e. small-scale farmers, living in and around important natural habitats. This thesis shows that the Zero Hunger programme does, however, have environmental impacts. In chapter 2 the largest societal benefits of the Zero Hunger programme occurred in the south of Brazil. In particular, protein production (soy and milk) has increased as a result of investment. At the same time, in the southern Pampa biome the largest losses of natural vegetation have occurred as a result of Zero Hunger (and PRONAF) programme participation. This suggests a clear trade-off between social and environmental aspects and threaten transitions to sustainable development. In the Cerrado and Amazon biome significant losses only occur with higher Zero Hunger (and PRONAF) investment levels. Chapter 2 also reveals, however, that these trade-offs do not always occur. Interestingly, in the neighbouring biome to the Pampa – the Atlantic Forest – Zero Hunger and the PRONAF sub-programme only drive increases in natural vegetation, regardless of investment level and despite also having experienced increases in food production and multi-dimensional poverty alleviation as a result of these programmes. The local study in chapter 3, where two of three municipalities were situated in the Atlantic Forest, also found that participation in the PAA programme was associated with less natural vegetation loss.

It is possible that while investment in the Atlantic Forest has promoted agricultural intensification, thus sparing agricultural land and enabling vegetation regrowth, investments in the Pampa has promoted expansion of agriculture and thus promoted loss of natural vegetation. Meyfroidt link such distinctions in response to differences in market demands and state that commodity crops with high global demand are the ones that tend to lead to agricultural expansion (Meyfroidt, 2018). Alternatively, the contrasting effects of Zero Hunger investment in these biomes could be due to different levels of conservation attention as that can deter farmers from converting natural vegetation into farm land. In particular, the Pampa has received very little conservation attention (Overbeck et al., 2007) while the Atlantic Forest has received a fair amount of attention from academics and governments (Pinto et al., 2014). More research into the precise mechanisms behind these trends, and why environmental trade-offs only occur in some locations, are needed before any conclusions can be made.

The programme in focus in chapter 4, the nationwide rural environmental registry (CAR) program, is primarily an environmental programme and falls within the Ministry of Environment (Siqueira et al., 2017), but it also has links to the Ministry of Agrarian Development and to private agricultural companies. In particular, credit offered to small-scale farmers (PRONAF) within the Ministry of Agrarian Development, and general rural credit offered through the National Rural Credit System (SNCR), now require farmers to show environmental compliance through CAR in order to gain access to credit (Assunção et al., 2017). Private companies involved in major commodities such as soy and beef also require evidence of compliance with environmental law (provided through CAR) in order to trade commodities (Alix-Garcia & Gibbs, 2017; Rausch & Gibbs, 2016). As such, cross-sectoral collaboration is used to encourage environmentally friendly behaviour amongst farmers. There is increasing interest in whether CAR thus influence livelihoods (Jung et al.; Siqueira et al., 2017).

The study in chapter 4 found that because of the links to credit and commodity markets the CAR affected change in area under pasture. However, heterogeneities in farm conditions between smaller and larger farmers (particularly their varied access to credit and these commodity markets) and leniency in environmental compliance expectancy (smaller farmers could still gain access to credit) have resulted in small and large farms responding differently as a result of CAR. In particular, while

CAR drove an increase in pasture area for smaller farms it drove a reduction in pasture area for larger farms. The increased leniency in environmental compliance for smaller farms was allowed in order not to deter small-scale farmers from registering for CAR, and to avoid negative livelihood effects caused by credit restrictions. Thus the environmental programme did have an explicit social focus and through the increased access to credit this likely benefitted the farmers. However, these benefits might have resulted in an environmental trade-off if the pasture expansion has come at the expense of natural vegetation. Overall though, area gained from a retraction in pasture area from larger farms might outweigh the losses caused by the expansion from smaller farms. In a global perspective, where large farms linked to global commodity markets continue to be main drivers of natural vegetation loss (Meyfroidt, 2018) enforcement of environmental compliance through a system such as CAR could lead to environmental benefits also elsewhere.

Targeting and policy design

Effective targeting is a main concern for social protection programmes, particularly to engage the poorest of the poor (Devereux, 2016; Schutter, 2013). The Zero Hunger sub-programmes and the CAR have all reported some challenges in engaging particularly poor or small-scale farmers (for CAR: Jung et al., 2017; for PAA: Milhorance et al., 2017; for Bolsa Familia: Soares et al., 2010; and for PRONAF: Vieira, 2015). The study in chapter 3 found clear evidence of differences in underlying characteristics between participants and non-participants in the Zero Hunger and three main sub-programmes. Bolsa Familia appears well targeted at poorer farmers in the study sample. Here participant households were younger and larger (indicating young families with children) and had less land. PRONAF and PAA, on the other hand, appear to primarily engage with more capable farmers. Here participants were more educated and had more land. Only about a third of farms with 2 hectare or less had participated at any point in these two programmes. This is in clear contrast to the “productive inclusion” axis stated by the Ministry of Social Development and Fight against Hunger (MDS) (UNDP-IPC, 2013).

In addition, household demographic and socio-economic characteristics were found to mediate the association between Zero Hunger sub-programmes and measures of food security and environmental outcomes. For instance, smaller households participating in PRONAF were positively associated to household food insecurity, while younger PAA participants were negatively associated with increased access in food. Active assistance from agricultural cooperatives and agricultural extension offices were identified as ways in which households with too little land-, labour- or experience could be assisted to participate and benefit from these programmes. Creating specific programme modalities for particularly vulnerable groups, such as the smallest or youngest farmers could also overcome some of the limitations they experience. In particular related to Africa there has been a concern about the ability of interventions to engage with and benefit the smallest farmers. Here the bottom 25% of small-scale farmers have less than 0.12 ha per capita. Rural extension services are also often lacking here (Jayne et al., 2014).

Another important mediating factor found was the simultaneous economic support from other social protection programmes, such as rural pensions or disability. Households participating in PRONAF or PAA who simultaneously received transfers from another social protection programme had markedly higher positive associations with increased food access and food self-sufficiency. Other national studies have also identified the importance of simultaneous economic support from other social protection programmes in order to lift poor Brazilian small-scale farmers out of poverty (Osorio et al., 2011; Vieira, 2015). A common characteristic for these programmes is that they are transferred regularly (every month) and they are equivalent to the minimum wage. The Zero Hunger sub-programme cash transfers, on the other hand, are often much smaller (Bolsa Famila in particular) and irregular (PAA and PRONAF). Given that most small-scale farmers face liquidity constraints (Devereux et al., 2008), which can hinder their optimal allocation of productive resources, a regular income such as a rural pension thus can make a big difference in their farm investment choices.

In the PAA inspired programmes implemented in Mozambique, the lack of regularity in PAA payments hindered poorer farmers from even participating. They simply could not withstand the insecurity and risks in participating (Milhorance et al., 2015). The capacity of farmers, particularly organizational capacity, was also identified as a fundamental factor in determining participation in these programmes (Milhorance et al., 2015). Same as in Brazil, however, cooperatives and associations were not well developed amongst poor (and dispersed) families. Despite several common traits between small-scale farmers in the two regions, Milhorance et al. also found several differences in terms of agricultural farming systems and agricultural trajectories. In addition, there is a major difference in the main source of food insecurity between Brazil and many Sub-Saharan countries. While in Brazil food insecurity is primarily due to a lack of economic access to food (Silva et al., 2011), in Sub-Saharan Africa lack food availability is still a major issue (Ingram, 2011). This highlights the fact that, the needs for specific interventions might vary across regions. As a key take home message is, thus, the importance in recognizing local context when diffusing programmes from one region to another (Milhorance et al., 2015). The importance of considering local context cannot be emphasized enough.

2. Recommendations for achieving sustainable development through social protection and environmental programmes which target small-scale farmers

1. A systems approach to sustainable development should be taken when designing and evaluating interventions for sustainable development. Integrated social protection programmes have been found able to deliver simultaneously on multiple social and environmental outcomes. In particular programmes which tackle major biases against small-scale farmers, such as market and credit restraints, are found to deliver on multiple outcomes on a large scale. Trade-offs

often occur, both between social outcomes and between social and environmental outcomes. To be able to pick up and act on these trade-offs, both intended and unintended outcomes of an intervention need to be evaluated.

2. In order for social and environmental protection programmes which target small-scale farmers to deliver on intended aims the basics need to be in place. This includes basic infrastructure such as sanitation system, school and health facilities, in addition to infrastructure relevant for agriculture. Care needs to be taken to avoid that investment in the intervention comes at the expense of necessary infrastructure investment as this scenario could undermine the effectiveness of the intervention.
3. Any intervention which engages with small-scale farmers need to be sensitive to the large heterogeneity within this population. What is defined as a small-scale farmer can vary greatly from region to region. If specific sub-groups within small-scale farmers appear particularly disfavoured to participate or benefit, i.e. young farmers or those producing on minimal land, programme modalities could be designed which direct special attention to this sub-group. Likewise, if certain farming systems appear particularly prone to unsustainable behaviour this behaviour could be mediated through supporting more agro-environmental production, conditioning participation on environmental compliance or engaging more actively with conservation institutions. Exclusion of assistance due to unsustainable behaviour could, however, have negative livelihood effects.
4. The presence and capacity of local support institutions should be assessed in areas where the intervention is planned. These services can be instrumental for the intervention to achieve intended social and environmental outcomes. Agricultural extension services and agricultural cooperatives are particularly relevant for small-scale farmer and environmental focused interventions. In particular, they can assist the poorest and less capable farmers in gaining access to, and benefit from, the programmes by helping with inscription processes and building organizational capacity. Programme participation through farm cooperatives or associations can also be particularly beneficial for smaller farmers. They can provide assistance and minimization of production risk. Preliminary institutional assistance to set up these cooperatives is often needed in areas dominated by poor small-scale farmers.
5. Cross-sectoral institutional collaboration is paramount to deliver on multiple sustainability outcomes. In particular, collaboration between social, agricultural and environmental sectors is needed for transitions towards sustainability. Even when such collaborations exist, trade-offs might still occur. However, if monitored appropriately these trade-offs can be picked up on and addressed.
6. For social protection programmes to effectively benefit small-scale farmers the economic incentives they offer should aim to relieve some of the liquidity constraints these farmer suffer

from. Liquidity constraints hinder optimal allocation of productive resources. If instead farmers can rely on regular payments they can plan their production more effectively

3. References

Ahmed, M. H., & Mesfin, H. M. (2017). The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: empirical evidence from eastern Ethiopia. *Agricultural and Food Economics*, *5*(6), 1–20. http://doi.org/10.1186/s40100-017-0075-z

Alix-Garcia, J., & Gibbs, H. K. (2017). Forest conservation effects of Brazil's zero deforestation cattle agreements undermined by leakage. *Global Environmental Change*, *47*(August), 201–217. http://doi.org/10.1016/j.gloenvcha.2017.08.009

Araújo, F. R. de, Araújo, M. A. D. de, Souza, F. J. V. de, Gurgel, I. L. P., & Gomes, A. C. C. (2018). Distribuição Espacial do Desempenho do Programa Bolsa Família: Um Estudo à Luz do IGD-M. *Revista de Ciencias Sociais, Rio de Janeiro*, *61*(3), 773–806.

Assunção, J., Gandour, C., Pessoa, P., & Rocha, R. (2017). Property-level assessment of change in forest clearing patterns : The need for tailoring policy in the Amazon. *Land Use Policy*, *66*(January 2016), 18–27. http://doi.org/10.1016/j.landusepol.2017.04.022

Barbier, E. B., & Burgess, J. C. (2017). The Sustainable Development Goals and the systems approach to sustainability. *Economics*, *11*, 1–22.

Barrientos, A. (2017). Design and rural context in antipoverty transfers: Implications for programme outcomes. *Global Food Security*, *12*(March 2016), 103–108. http://doi.org/10.1016/j.gfs.2016.09.002

Cecchini, S., & Madriaga, A. (2011). *Conditional Cash Transfer Programmes: The recent experience in Latin America and the Carribbean*. Cuadernos de la CEPAL.

Devereux, S. (2016). Social protection for enhanced food security in sub-Saharan Africa. *Food Policy*, *60*, 52–62. http://doi.org/10.1016/j.foodpol.2015.03.009

Devereux, S., Sabates-Wheeler, R., Guenther, B., Dorward, A., POULTON, C., & Al-Hassan, R. (2008). *Linking Social Protection and Support to Small Farmer Development*. Rome.

Eusebio, G. dos S., Maia, A. G., & Silveira, R. L. F. da. (2016). Impact of microcredit on small-farm agricultural production: evidence from Brazil. In *Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, MA, July 31-August 02*.

FAO. (2018). SOFI 2018 - The State of Food Security and Nutrition in the World. Retrieved September 27, 2018, from http://www.fao.org/state-of-food-security-nutrition/en/

Hall, A. (2008). Brazil's Bolsa Familia : A Double-Edged Sword? *Development and Change*, *39*(5), 799–822.

Hazell, P., Poulton, C., Wiggins, S., & Dorward, A. (2007). *The Future of Small Farms for Poverty*

Reduction and Growth. Washington, DC.

Helfand, S. M., Moreira, A. R. B., & Jr., E. W. B. (2015). *Agricultural Productivity and Family Farms in Brazil : Creating Opportunities and Closing Gaps*.

Ingram, J. (2011). A food systems approach to researching food security and its interactions with global environmental change. *Food Security*, *3*(4), 417–431. http://doi.org/10.1007/s12571-011-0149-9

Jayne, T. S., Chamberlin, J., & Muyanga, M. (2014). Emerging Land Issues in African Agriculture : Poverty Reduction Strategies. *Stanford University's Global Food Policy and Food Security Symposium Series*.

Jung, S., Rasmussen, L. V., Watkins, C., Newton, P., & Agrawal, A. (2017). Brazil's National Environmental Registry of Rural Properties: Implications for Livelihoods. *Ecological Economics*, *136*, 53–61. http://doi.org/10.1016/j.ecolecon.2017.02.004

Meyfroidt, P. (2018). Trade-offs between environment and livelihoods: Bridging the global land use and food security discussions. *Global Food Security*, *16*, 9–16. http://doi.org/10.1016/j.gfs.2017.08.001

Milhorance, C., Sabourin, E. P., & Bursztyn, M. (2015). International Conference of Public Policy Potential and Limits to Diffusing Brazil ' s Zero Hunger Strategy in Sub - Saharan Africa : The Case of Mozambique, (July).

Mojo, D., Fischer, C., & Degefa, T. (2015). Social and environmental impacts of agricultural cooperatives: Evidence from Ethiopia. *International Journal of Sustainable Development and World Ecology*, *22*(5), 388–400. http://doi.org/10.1080/13504509.2015.1052860

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., … Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, *520*(7545), 45–50. http://doi.org/10.1038/nature14324

Osorio, R. G., Souza, P. H. G. F. de, Soares, S. S. D., & Oliveira, L. F. B. de. (2011). *Perfil da pobreza no Brasil e sua evolução no período 2004-2009*.

Overbeck, G. E., Müller, S. C., Fidelis, A., Pfadenhauer, J., Pillar, V. D., Blanco, C. C., … Forneck, E. D. (2007). Brazil's neglected biome: The South Brazilian Campos. *Perspectives in Plant Ecology, Evolution and Systematics*, *9*(2), 101–116. http://doi.org/10.1016/j.ppees.2007.07.005

Perfecto, I. Vandermeer, J. and Wright, A. (2009). *Nature's matrix: Linking agriculture, conservation and food sovereignty*. London: Earthscan. Retrieved from http://climateandcapitalism.com/2012/10/17/natures-matrix/

Perfecto, I., & Vandermeer, J. (2010). The agroecological matrix as alternative to the land-sparing/agriculture intensification model. *Proceedings of the National Academy of Sciences*, *107*(13), 5786–5791. http://doi.org/10.1073/pnas.0905455107

Pinto, S., Melo, F., Tabarelli, M., Padovesi, A., Mesquita, C., de Mattos Scaramuzza, C., … Brancalion, P. (2014). Governing and Delivering a Biome-Wide Restoration Initiative: The Case of Atlantic Forest Restoration Pact in Brazil. *Forests*, *5*(9), 2212–2229. http://doi.org/10.3390/f5092212

Piperata, B. A., McSweeney, K., & Murrieta, R. S. (2016). Conditional Cash Transfers, Food Security, and Health: Biocultural Insights for Poverty-Alleviation Policy from the Brazilian Amazon. *Current Anthropology*, *57*(6), 806–826. http://doi.org/10.1086/688912

Rausch, L. L., & Gibbs, H. K. (2016). Property Arrangements and Soy Governance in the Brazilian State of Mato Grosso : Implications for Deforestation-Free Production. *Land*, *5*. http://doi.org/10.3390/land5020007

Samberg, L. H., Gerber, J. S., Ramankutty, N., Herrero, M., & West, P. C. (2016). Subnational distribution of average farm size and smallholder contributions to global food production. *Environmental Research Letters*, *11*(12), 1–11. http://doi.org/10.1088/1748-9326/11/12/124010

Sayer, J., Sunderland, T., Ghazoul, J., Pfund, J.-L., Sheil, D., Meijaard, E., … Buck, L. E. (2013). Ten principles for a landscape approach to reconciling agriculture, conservation, and other competing land uses. *Proceedings of the National Academy of Sciences*, *110*(21), 8349–8356. http://doi.org/10.1073/pnas.1210595110

Schutter, O. De. (2013). *Interim report of the Special Rapporteur on the right to food*.

Silva, J. G. da, Grossi, M. E. Del, & França, C. G. de. (2011). *The Fome Zero (Zero Hunger) Program: The brazilian experience*. (J. G. da Silva, M. E. Del Grossi, & C. G. de França, Eds.). Brasilia.

Siqueira, E. de, Franceschini, M., Grisolia, G., Milanez, M., & Nasuti, S. (2017). The Rural Environmental Registry (CAR) - an Opportunity for Integrated Environmental Land Management for Traditional Peoples and Communities in Brazil? In *Anual World Bank Conference on Land and Poverty*. Washington DC.

Smith, L. C., & Haddad, L. (2015). Reducing Child Undernutrition: Past Drivers and Priorities for the Post-MDG Era. *World Development*, *68*(1), 180–204. http://doi.org/10.1016/j.worlddev.2014.11.014

Soares, F. V., Ribas, R. P., & Osorio, R. G. (2010). Evaluating the Impact of Brazil's Bolsa Familia: Cash transfer programs in comparative perspective, *45*(2), 173–190.

Soares, S., Souza, L. De, Silva, W. J., & Silveira, F. G. (2016). *Poverty profile : the rural North and*. Brasilia.

Tubiello, F. N., Salvatore, M., Ferrara, A. F., House, J., Federici, S., Rossi, S., … Smith, P. (2015). The Contribution of Agriculture, Forestry and other Land Use activities to Global Warming, 1990-2012. *Global Change Biology*, *21*(7), 2655–2660. http://doi.org/10.1111/gcb.12865

UNCTAD. (2015). Commodities and Development Report 2015: Smallholder Farmers and Sustainable Commodity Development. *United Nations Conference on Trade and Development*, 1–20. http://doi.org/UNCTAD/SUC/2014/5

UNDP-IPC. (2013). *Structured Demand and Smallholder Farmers in Brazil : the Case of PAA and*

PNAE. Brasilia.

Verhofstadt, E., & Maertens, M. (2015). Can agricultural cooperatives reduce poverty? Heterogeneous impact of cooperative membership on farmers' welfare in Rwanda. *Applied Economic Perspectives and Policy*, *37*(1), 86–106. http://doi.org/10.1093/aepp/ppu021

Vieira, I. (2015). *Policies for Rural Development : an Analysis Focusing on the North and Northeast Regions of Brazil*. Brasilia.

Appendix

1. Antipode Book Review

M. Jahi Chappell, *Beginning to End Hunger: Food and the Environment in Belo Horizonte, Brazil, and Beyond*, Oakland: University of California Press, 2018. ISBN: 9780520293083 (cloth); ISBN: 9780520293090 (paper); ISBN: 9780520966338 (ebook)

Hunger has been present in most societies throughout history, to the point where one might think it's a natural, albeit unwanted, part of human society. At the same time, eradicating hunger has been at the top of national and international agendas for decades, featuring as a main goal in both the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs). As attention to the prevalence of hunger has increased so has our common understanding of it evolved. Nowadays concepts like chronic and acute malnutrition, micronutrient deficiencies (also known as "hidden hunger") and food insecurity are all linked to hunger. And as our understanding has evolved a myriad of interventions to try and eradicate hunger have been put in place. Still millions of people around the world go hungry every day. Indeed, one might start to think eradicating hunger is an impossible task.

It is within this setting that M. Jahi Chappell's book *Beginning to End Hunger* sits. It's an eye-opening book both for those working on matters of hunger and for those who don't. We all have a relationship with food and preconceived notions about how food and food shortages function in the world. From the first page Chappell questions the knowledge and our main taken-for-granted truths about hunger. Drawing from a broad range of literature he lays out the main views and ideologies around hunger and food shortage throughout time and picks apart common misconceptions about the causes and prevalence of hunger and food insecurity. In true critical geography spirit he further delves into why these misconceptions have held up for so long, particularly by asking the question of who benefits from the status quo. Even more importantly he does not stop at critique, but offers a real-life example where drastic reductions of hunger have been achieved and lays out the conditions through which this was made possible.

In Chapter 1, "Food and Famine Futures, Past and Present", Chappell explores the place of hunger in our global food system, and we are introduced to two key concepts that follow us throughout the book: [i] "active optimism" – the idea that hunger *can* be ended; and [i] "*Cui bono?*", i.e. who is benefiting from the status quo? Chapter 2 goes through the evolution of frameworks for analysing hunger, and serves as a useful background to Chapter 3 where we are introduced to the Brazilian city of Belo Horizonte, the birthplace of a range of food security policies considered as highly successful both nationally and world-wide. To me Chapter 4 stands out as particularly informative in that it attempts to explain *how* these ambitious policies were born and established in Belo Horizonte in the 1990s. It moves beyond a description of the nuts and bolts of these programmes, shedding light on the importance of timing, institutions and political will for the birth and success of policies. In Chapter 5, "Farm, Farmer, and Forest", the focus is moved to the rural setting, and to food security programmes aimed at small-scale farmers with the aim of improving food security for themselves and a growing urban population. In a particularly refreshing move the chapter examines whether in addition to food security and farmer livelihood benefits the programmes may also have a positive effect on the environment. Chapter 6 summarizes with main findings from the book and lifts its gaze outwards to how the experience in Belo Horizonte and Brazil can be informative elsewhere.

A main strength of Chappell's book is that it effectively engages the reader and challenges basic taken-for-granted notions about the cause and perpetuation of hunger. Many of us will have heard the response when asked to achieve a seemingly impossible task – "…and next we'll solve world hunger" (p. 4) – or been guilty of having held the fatalistic belief that because our societies still suffer from starvation and hunger it must be an inevitable part of them. He delves into perhaps the largest misconception around food insecurity which in certain fields still dominates discussions, i.e. that all we need to do is produce more food. For instance, when placed under scrutiny by Chappell the perceived scientific "fact" that we need 70-100% increases in food production to feed future populations may be closer to a mere 6% increase needed, and, in fact, when looking at previous improvements the largest drops in malnutrition have actually been achieved by improvements in water and sanitation systems, and not from increasing food supply.

Critically scrutinizing information taken as "fact" is none the less important when assessing the evidence bases we use to determine the success and effectiveness of a programme or policy. It's a major task to prove cause or effect of an intervention in the real world, inherently difficult given that we can never truly know what the world would have looked like without it, and given the difficulty in isolating its impact from the range of alternative explanations present in the environment (see Guo and Fraser [2015] on the idea of "counterfactuals"). In that sense there is an important distinction to be made between monitoring progress of an outcome after an intervention was put in place (and uncritically assigning a causal link between the two) and thoroughly engaging with and unpicking impacts of the specific intervention from alternative explanations. Likewise, questions like who is benefiting and who is not, and what the possible unintended consequences or trade-offs of the intervention are, are vital to consider.

When examining the food security secretary in Belo Horizonte and the series of food programmes which evolved under its supervision Chappell does not shy away from exploring the nuances of the food policy. He shows areas where the multiple interventions clearly have generated positive change in people's access to food, and highlights especially how creating *agency* for people (a main pillar in the 5 A's food security framework developed by Cecilia Rocha) have made a positive impact on people's food security. At the same time he also explores who hasn't been able to benefit from the programmes, and in some cases questions whether those who have participated were those most in need of assistance. He also reminds us of the importance of including the factor of time into the equation, highlighting that the institutions so vital for the success of an intervention evolve and change over time, for good and for bad, and achieving food security is really a continuous process. In his own words, "…there always remains more to be done in an area such as food security,…[it] is a marathon project" (p. 92), or as stated by staff of the food secretariat, "'success'…would imply that the secretariat had completed its job and that food insecurity was no longer a problem" (ibid.). This leads me to think the whole idea of referring to an intervention as a success may in itself be problematic.

Lastly, because of the unpredictability of the world and the numerous interactions that go on within it, when assessing an intervention it is also important to consider both intended and unintended impacts. Chappells' ant study in Chapter 5 is therefore particularly interesting. Rather than the more commonly explored link on how biodiversity can influence food security the study considers the other direction, i.e. how a food security programme may positively impact biodiversity. I In doing so he challenges another commonly held view: that human development has to come at the expense of the environment. As Chappell points out: "what we believe…has profound effects on notions of reality and the interventions we subsequently propose" (p.12), and therefore challenging such common beliefs and making sure they hold up to scrutiny is vital in our quest to achieve universal food security. And it is because of Chappell's contribution in doing just that, that I believe this book is indeed a step towards *Beginning to End Hunger*.

References

Guo S and Fraser M W (2015) *Propensity Score Analysis: Statistical Methods and Applications* (2nd edn). London: Sage

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Weblink:
https://radicalantipode.files.wordpress.com/2018/09/book-review_dyngeland-on-chappell.pdf

2. Farm Survey

0. Identificação dos entrevistadores e entrevistas

[1]ID do entrevistador:	Data (dia, mês, ano):	Hora (XX:XX):
[2]ID municipio:	[3]ID do distrito:	Número do questionário:
Village Name: Nome da comunidade/bairro:		

[1]1. Cecilie =1, Assistant 1 =2, Assistant 2 = 3
[2] **Municipios:** Montes Claros = 3143302, Ouro Verde do Minas = 3146206, Ponte Nova = 3152105, São Franciso = 3161106
[3]**Distritos Montes Claros:** Montes Claros = 05, Aparecido do Mundo Novo = 08, Ermidinha = 10, Miralta = 15, Nova Esperança = 20, Panorâmica = 22, Santa Rosa de Lima = 25, São João Da Vereda = 30, São Pedro Da Garça = 35,
Vila Nova de Minas = 40
[3]**Distritos Ouro Verde de Minas:** Ouro Verde = 05
[3]**Distritos Ponte Nova:** Ponte Nova = 05, Rosário do Pontal = 13, Vau Açu = 15
[3]**Distritos São Francisco:** São Franciso = 5, Lapa do Espírito Santo = 12, Morro = 15, Retiro = 18, Santa Isabel de Minas = 30, Santana de São Francisco = 35, Travessão de Minas = 40

Consentimento

Meu nome é ________________. Estou trabalhando com uma pesquisa de um doutorado da universidade de Sheffield na Inglaterra
que trata das práticas agrícolas no Brasil, particularmente as mudanças na produção agrícola e na segurança alimentar. Por isso, gostaria de lhe fazer alumas perguntas sobre você e a sua propriedade. Todos os dados coletados serão utilizados unicamente para o propósito desta pesquisa. Suas respostas serão anônimas em qualquer análise ou relatório de pesquisa publicados. Esta pesquisa é voluntária e você pode interrompê-la a qualquer momento. Da mesma forma, você também pode escolher não responder alguma questão com a qual não se sinta confortável.
Nós agradecemos muito a sua cooperação e o seu tempo.

1. Você gostaria de participar dessa pesquisa?
   _____1.Sim, _____2. Não

3. Quantos membros moram na propriedade?

   Uma propriedade/domicìlio significa todas as pessoas que moram na mesma casa/conjunto de moradias e que compartilham recursos da propriedade, como alimentares ou de renda

   ____

4. Quantos membros do propriedade (incluindo você) dependem da mesma renda?

   ____

	Nome	Sexo 1=masc 2=fem	Idade	Parentesco com o chefe 1=Chefe 2=Cônjuge,companheiro(a) 3=Filho(a), enteada 4=Irmão,irmã 5=Mãe,Pai 6=Tio(a) 7=Sobrinho(a) 8=Neto,Neta 9=Genro,Nora 10=Primo(a) 11=Sogro(a) 12=Avô, Avó 13=Cunhado(a) 99=Outros	Etinia (cor) 1=Branco 2=Preto 3=Amarelo 4=Indigena 5=Pardo 6=Outros	Frequenta escola? 1=Sim 2=Não	Vc sabe ler e escrever (mais que seu nome)? 1=Sim 2=Não	Quantos anos de Estudos formais Sr(a) tem? (incluindo Pre)	No dias perdidos devido a problemas de saúde?
1									
2									
3									
4									
5									
6									
7									
8									
9									
10									
11									
12									
13									
14									
15									

5. **Informante (nome)?____**

7. Há quanto tempo o chefe trabalha nesta propriedade ?_______________anos

8. Há quanto tempo o chefe da família mora neste município?___________
    a. Há quanto tempo o chefe mora nesta comunidade/bairro?__________

9. Você atualmente é membro de alguma cooperativa ou associação agrícola?
___1.sim, **pule para pergunta 13**,___2.não

11. Por que o Sr(o) nunca se afiliou a uma cooperative/associação? (então pule **para pergunta 14**)
____
____

13. Quais as principais mudanças ocurridas na propriedade a partir da participação na cooperative/associação agrícola?____
____

14. Você tem um amigo ou membro da família que trabalha no escritório do EMATER?
___1.sim, ___2.não

<u>Parte B: O meio ambiente e a mudança do uso da terra</u>

17. 1. Quanta Terra seu domicilio possui e/ou administra nesse municipio? ___________unidade___________

17. Quanta terra que seu domicilio possui e/ou administra neste municipio é irrigada?_______________unidade

17.2. Seu domicilio aluga alguma parcela de suas terras nesse municipio para outros fazendeiros? Quanto?________unidade_______

c. Por favor dê detalhes sobre os pedaços de terra que seu domicilio possui e/ou administra nesse municipio, como tamanho, tipo de propriedade e uso

Códigos de unidade: 1=Hectares, 2=Alqueires, 3=Metros Quadrado, 4=Pes

NO	Categorias	Propriae gerida	Unid	Alugada de Terceiros	Unid	Trabalhando como meerio	Unid	Privada dada a meeiros (Só preg cultura planta a frutifra no geral)	Unid
1	Cultura de rendimento (planta)								
2	Cultura de rendimento (árvores frutiferas)								
3	Cultivo de subsistência (planta)								
4	Cultivo de subsistência (árvores frutiferas)								
5	Pastagem natural								
6	Pastagem plantada								
7	Em repouso								
8	Àrvores de Eucalipto plantadas								
9	Outros árvores plantadas para madeira/outros produtos (não fruta)								
10	Árvores nativas plantadas não para colher produtos								
11	Floresta natural(não-plantada)								
12	Outro, explique								

Q17.5 Seu domicilio possui ou administra terra em outro Municipio? 1=Sim, 2=Não, **pule para Q18**

Nome de Municipio____

17.0 Quanto terra seu domicilio possui e/ou administra em esse outro municipio?
municipio?_______________unidade_____________
17. Quanto terra que seu domicilio possui e/ou administra em esse outro municipio éirrigada? _______unidade
17.N Seu domicilio aluga alguma parcela de suas terras em esse outro municipio para outras fazendeiros?
Quanto? ______________________unidade___________________

Códigos de unidade: 1=Hectares, 2=Alqueires(4.84ha), 3=Metros Quadrado, 4=Pes

NO	Categorias	Propria e gerida	Unid	Alugada de Terceiros	Unid	Trabalhando como meerio	Unid	Privada dada a meeiros (Só preg cultura planta a frutifra no geral)	Unid
1	Cultura de rendimento (planta)								
2	Cultura de rendimento (árvores frutiferas)								
3	Cultivo de subsistência (planta)								
4	Cultivo de subsistência (árvores frutiferas)								
5	Pastagem natural								
6	Pastagem plantada								
7	Em repouso								
8	Àrvores de Eucalipto plantadas								
9	Outros árvores plantadas para madeira/outros produtos (não fruta)								
10	Árvores nativas plantadas não para colher produtos								
11	Floresta natural(não-plantada)								
12	Outro, explique:								

18. Como você avalia a intensidade da sua atividade agrìcola hoje comparada com o começo da sua administração ou trabalho na propriedade? (exemplo da intensidade elevada: mais máquinas ou mais insumos na mesma área) **(se 3 pule para Q20)**

Intensity/Intensidade					
1. muito mais baixa	2. um pouco mais baixa	3. mais ou menos a mesma	4. um pouco mais elevada	5. muito mais elevada	Nao se aplica porque não tenho cultura

19. Qual foi o mecanismo principal para essa mudança? (ex: mais ou menos máquinas)
____

19.2 Qual foi a razão principal para essa mudança? (ex de razão principal para mais insumos, por que o solo ficou esgotado, our por que teve mais dinheiro para investir)
____

20. Como você avalia a intensidade da sua atividade pecuária hoje comparada com o começo da sua administração ou trabalho da propriedade? (ex. de intensidade elevada: mais alimentação ou mais animais na mesma área) **(se 3 pule para Q22)**

Intensity/Intensidade					
1.muito mais baixa	2.um pouco mais baixa	3.mais ou menos a mesma	4.um pouco mais elevada	5.muito mais elevada	Não se aplica porque não tenho animais/pastagem

21. Qual foi o mecanismo principal para essa mudança na intensificação pecuária? (ex: mais animais na mesma área)____

21.2 Qual foi a razão principal para essa mudança? (ex de razão para mais animais, por que teve mais dinheiro para investir)____

22. Desde que você começou a trabalhar ou gerenciar a propriedade, houve alguma mudança no tamanho da terra ou no uso do solo?
Cite ao maximo 5 das mudanças mais importantes
(OBS: ex Plantio de eucalipto é mudança no uso, trocar mata nativa por pasto tambem)
___1.sim, ___2.não, **pule para pergunta 24**

23. Se sim, qual foi a mudança, quando foi e por quê?

23.1As mudanças foram para mais ou para menos? 1.menos/diminuiu, 2.mais/aumentou	**23.2 Ano ou** 99. cada ano	**23.3Tipo de mudanã** 1. compra, 2.venda de parte da terra 3. aluguel, 4. suspenção de aluguel, 5. mudança de terra mesma	**23.4Quanto foi a acrescida ou diminuida da terra?**	**23.5Unidade** **1. hectares** **2. alqueires** **3.metros quadrados** **4.pes**	**23.6Uso anterior da terra** 1.Cultura agrícola do domicílio, 2.Cultura agrícola do meeiro, 3.Cultura agricola com árvores (ex: fruta), 4.Pastagem natural, 5.Pastagem plantada, 6.Plantação eucalipto, 7.Plantação outro, 8.Floresta natural, 9.Cerrado, 10. Várzea, 11.Edificações (ex:casa, galpoes,currais), 12.Açudes 13.Outros usos	**23.7Uso novo da terra** 1.Cultura agrícola do domicílio, 2.Cultura agrícola do meeiro, 3.Cultura agricola com árvores (ex: fruta), 4.Pastagem natural, 5.Pastagem plantada, 6.Plantação eucalipto, 7.Plantação outro, 8.Floresta natural, 9.Cerrado, 10. Várzea, 11.Edificações (ex:casa, galpoes,currais), 12.Açudes 13.Outros usos	**23.8 Razão principal (sempre escreve!)** 1. falta de mão de obra disponível para seguir no mesmo jeito, 2. falta de dinheiro para seguir no mesmo jeito, 3. falta de rentabilidade de seguir no mesmo jeito, 4. para produzir mais no mesmo produto 5. para produzir um novo produto 6. Outro, explique

Se a pessoa plantou eucalipto pule para pergunta 25

EXTRA: Eucalipto

24. Por que você nunca plantou eucalipto?
____
____

25. Qual é a probabilidade que você vir plantar eucalipto no futuro?
    ___1.improvável que vou plantar
    ___2.pouco provável que vou plantar
    ___3.talvez vou plantar
    ___4.muito provável que vou plantar
    ___5.extremamente provável que vou plantar

Se o domicilio está plantando eucalipto agora (ex: não coletou) pule para Q27
Se o domicilio nunca plantou eucalipto pule para Q38

26. Se você plantou anteriormente, mas parou, por que parou?
____
____

27. Como financiou o plantio?
____
____

28. 1. Você pulveriza(va) o eucalipto com Insecticida? _____1.Sim, _____2.Não, **pule para 28.3.**
    2. Quantas vezes por ano?_________ (0-12 ou 99=so epoca da plantio)

    3.Você aplica(va) Adubo no eucalipto?_____1.Sim,______2.Não, **pule para 29.1**
    4. Quantas vezes por ano?________(0-12 ou 99=so epoca da plantio)

29. 1. Você pulveriza(va) o eucalipto com herbicida? _________1.Sim, ________2.Não, **pule para Q30**
    2. Quantas vezes por ano?__________ (0-12 ou 99=so epoca da plantio)

30. Você irriga o eucalipto? ___1.sim, ___2.não, **pule para pergunta 32**

31. Quantos anos do ciclo de plantação você irriga?_________________(1-7 anos)

32. Você já colheu? ___sim, **pule para pergunta 34**, ___2. não

33. Quando você espera colher?_____________________________ano (pule para pergunta 37)

34. 1-2. Quanta madeira você vendeu, em quantidade (e unidade)?_________________unidade___________
    3. Qual foi o rendimento total?_______________________________R$

35. Qual foi o uso dada a madeira, se uso múltiplo, qual proporção de cada uso?
    1.papel____%, 2.carvão____%, 3.madeira____%, 4. óleo_____%, ________________6.outro uso____%,
    Não sei____%

36. Pensando nas suas expectativas iniciais, como você avalia a rentabilidade do plantio de eucalipto?
    ___1. muito menos rentável, ___2.um pouco menos rentável, ___3.mais ou menos na mesma,
    ___4.um pouco mais rentável,___5.muito mais rentável

37. Houve algum impacto do plantio de eucalipto?
____
____

Parte C: Acesso aos Bens

38. Agora vamos falar sobre os bens do domicilio. Por favor responda o número de bens que possui

Item	Número possuído	Item	Número possuído
1. Comunicação		4. Mobilidade	
38.1 Telefone (fixo)		38.40 Bicicleta	
38.2 Telefone (celular)		38.41 Moto	
38.3 Rádio		38.42 Automóvel	
38.4 Televisão		38.43 Animais de montaria	
38.5 Internet (em casa)		38.44 Animais de carroça para transporte	
2. Edificios		38.45 Canoa, barco	
		38.46 Outra medida de transporte, explique	
38.6 Casas para morar		5. Eletrodomésticos	
38.7 Armazem agrìcola		38.47 Geladeira	
38.8 Alojamento para animais (granja,curral,galinheiro etc.)		38.48 Freezer (não considerar o freezer da geladeira duplex)	
38.9 Galpões de Processamento(ex: laticìnio, alambiques)		38.49 Vídeocassete, DVD, BlueRay	
38.10 Estufa		38.50 Ventilador elétrico	
38.11 Roçadeiras		38.51 Ar-condicionado	
		38.52 Máquina de costura	
		38.53 Gerador	
		38.54 Fogão elétrico ou a gás	
		38.55 Fogão à lenha	
		38.56 Microondas	
		38.57 Computador, Notebooks	
		38.58 Outro electrodomestico, explique:	
3. Máquinas e equipamentos agrícolas			
38.12 Motosserra			
38.13Pulverizador de planta		38.27 Uso coletivo: Pulverizador de planta	
38.14 Pulverizador de. animal		38.28 Uso coletivo: Pulverizador de Animal	
38.15 Sistema de Irrigação			
38.16 Carroça		38.29 Uso coletivo: Carroça	
38.17 Arado		38.30 Uso coletivo: Arado	
38.18 Debulhador		38.31 Uso coletivo: Debulhador	
38.19 Trator		38.32 Uso coletivo: Trator	
38.20 Ciladera		38.33 Uso coletivo: Ciladera	
38.21 Secadora de Grãos		38.34 Uso coletivo: Secadora de Grãos	

38.22 Colheitadeiras		38.35 Uso coletivo: Colheitadeiras	
38.23 Cilo		38.36 Uso coletivo: Cilo	
38.24 Fábrica de Ração		38.37: Uso coletivo: Fábrica de Ração	
38.25 Tanque de refriamento individual		38.38 Uso coletivo: Tanque de refriamento	
38.26 Outro máquina;equipamento agricola, Explique:		38.39Uso coletivo: Outro máquina/equipamento agricola de uso coletivo, eqplique:	

<u>Construção da sua Residência</u>

39. Quantos cômodos existem em sua residência? (não inclue banheiros, veranda, garagem)_______

40. Qual material predominante nas paredes de sua casa?
_____1.Tijolo,______2.Madeira,_____3.Papelão,______4.Plastico,______5.Lona,_____6.Pedra,
_____7.Metal,______8.Sape/Vime,______10.Concreto/Cemento, _________11.Adobe

41. Qual material predominante no piso de sua casa? (floor)
_____1.Cerámica,______2.Cimento,_________3.Terra,_________4.Ardosia,_________5.Madeira
42. Qual material predominante no telhado da sua casa? (roof)
_____1.Telha de barro,______2.Zinco,_______3.Palha,______4.Madeira,_______5.Papelão,
_____6.Plastico,_______7.Laje,________8.Lona,_______9.Amianto

43. Qual tipo de banheiro tem em sua residência?

1. Fossa/Vasos sem descarga	___1.1 Dentro, ___1.2 fora	___1.3 Privado, ___1.4Compartilhado
2. Vaso com descarga conectado a fossa rudimentaria	___2.1 Dentro, ___2.2 fora	___2.3 Privado, ___2.4 Compartilhado
3. Vaso sanitário com descarga conectado a fossa séptica	___3.1 Dentro, ___3.2 fora	___3.3 Privado, ___3.4Compartilhado
4. Vaso sanitário com descarga conectado a rede de esgotos	___4.1 Dentro, ___4.2 fora	___4.3 Privado, ___4.4 Compartilhado
6. Outro, explique __________________________________)	___5.1 Dentro, ___5.2 fora	___5.3 Privado, ___5.4 Compartilhado

____5.Nenhum banheiro

45. A agua consumida no domicilio é proveniente de?
_______1. Rede geral publica, ______2.Poço privado, _______3.Poço compartilhado,
_______4.Rios , corregos e lago,_________5.Cistena,________6.Mina de agua(nascente)

45.1 Se a água não é canalizada para a casa, qual é o tempo gasto em minutos para a fonte de agua?
_______min (**0 = agua é canalizada, pule para Q46**)

45.2 Qual meio de transporte utilizao para busca agua?
____1. A pé, ____2. Animais de carge, _____3.Veiculos(moto, carro etc.), ____4.Bicicleta

47. Qual é a principal fonte de energia da sua casa?
______1. Electricidaded da rede, _______2.Electriciade de Gerador,_______3.Querosene,________4.Óleo,__________5.Electricidade de Energia solar,
______7. Velas, ________8.Não tem

48. Qual tipo de combustível você usa mais para cozinhar?

______1. Gás encanado ou de butijão,______2.Carvão,_______3.Lenha,__________4.Esterco, ______5. Elétrica,________6.Bloquetes de biomassa,_________7.Querosene, 8.Outros_______

49. Esta é uma pergunta delicada mas preciso perguntar.
    Algum membro do domicílio faleceu nos últimos 12 meses?
    ___1.sim, ___2.não, **pule para Q51**

50. Quantos anos tinha? ______________anos

Parte D: Segurança alimentar do domicílio dentro nos últimos 12 meses

51. LEIA: Agora vou ler para você algumas perguntas sobre a alimentação em seu domicílio (sua propriedade). Elas podem ser parecidas umas com as outras, mas é importante que você responda todas elas. Para cada pergunta, indique a frequência conforme os itens a seguir: "nunca", "muito poucas vezes", "algumas vezes", "quase sempre" ou "sempre". Também indique quais meses isso ocorreu.

N/O	**Pergunta**	**Frequência:** 1.Nunca, 2.Muito poucas vezes, 3.Algumas vezes, 4.Quase sempre, 5.Sempre	**Em quais mes ocorreu?** (1-12) (se eles responde 1 não e necessario perguntar por mes)
1	Durante os últimos 12 meses, com que frequência os moradores deste domicílio tiveram a preocupação de que os alimentos acabassem antes de poderem comprar ou receber mais comida?		
2	Durante os últimos 12 meses com que frequência os alimentos acabaram antes que os moradores deste domicílio tivessem dinheiro para comprar comida ou tivessem outras fontes de alimento?		
3	Durante os últimos 12 meses com que frequência os moradores deste domicílio deixaram de ter uma alimentação saudável e nutritiva porque não havia dinheiro para comprar comida ou não havia outras fontes de alimento?		
4	Durante os últimos 12 meses com que frequência os moradores deste domicílio comeram apenas alguns poucos tipos de alimentos porque o dinheiro ou outras fontes de alimento acabaram?		
5	Durante os últimos 12 meses com que frequência os moradores deste domicílio deixaram de fazer alguma refeição porque não havia dinheiro para comprar comida ou não havia outras fontes de alimento?		
6	Durante os últimos 12 meses com que frequência os membros deste domicílio comeram menos do que acharam que devia, porque não havia dinheiro para comprar comida ou não havia outras fontes de alimento?		
7	Durante os últimos 12 meses com que frequência os membros deste domicílio sentiram fome, mas não comeram , porque não havia dinheiro para comprar comida ou não havia outras fontes de alimento?		
8	Durante os últimos 12 meses com que frequência os membros deste domicílio ficaram um dia inteiro sem comer, porque não havia dinheiro para comprar comida ou não havia outras fontes de alimento?		

Se respondeu 1.Nunca a totas as perguntas emcima, pule par pergunta 54)

52. Quais foram as 3 razões principais para não ter comida suficiente para o seu domicilio? (ou se você só teve preocupação de não ter comida, qual foi as 3 razões principais para isso?)
____
____
____

54. Qual foi o percentual do rendimento do domicílio que foi gasto na compra de alimentos nos últimos 12 meses? (ex 10%) ______%

55. Qual é a proporção (%) do consumo alimentar do domicílio nos últimos 12 meses que veio dos seguintes fontes?
1. Doações/Troca com outra propriedade, familioa ou amigos___________%
2. Refeições escolares gratuitas fornecida pelo PNAE (merenda escolar)________%
3. Outras doações (ex comita gratuita de instituções públicas, explique_________________)?______%
4. Colheita de produtos fora da propriedade/bosque (ex:mel, fruta, carne)? ____%
5. Alimento produzido na sua propriedade________%
6. Alimento comprado_______%

56. Como mudou o acesso a alimentação (em termos de quantidade) de seu domicílio, desde o começo de trabalho/gerencia dessa propriedade até hoje? (**se 3, pule para pergunta 58**)

1.muito mais baixa agora	2.um pouco mais baixa agora	3.mais ou menos a mesma agora	4.um pouco mais elevada agora	5.muito mais elevada agora

57. Qual foi a razão principal para essa mudança de accesso a alimentação (quantidade)?
____
____

1.Aumentou a renda a partir de nossa produção (sem causa específica para o aumento) com que pudemos comprar alimentação,
2.Aumentou a produção (sem causa especifica para o aumento) para sustencia,
3.Aumentaram a quantidade de alimentos disponíveis no mercado,
4.Diminuiu a quantidade de alimentos disponíveis no mercado,
5.Outro, explique

58. Como mudou o acesso a alimentação variada de seu domicílio, desde o começo de trabalho/gerencia dessa propriedade até hoje? (**se 3, pule para pergunta 60**)

1. muito mais baixa	2.um pouco mais baixa	3.mais ou menos a mesma	4.um pouco mais elevada	5.muito mais elevada

59. Qual foi a principal razão para essa mudança de accesso a alimentação variada?
____
____

1.Aumentou a renda a partir de nossa produção (sem causa específica para o aumento) com que pudemos comprar alimentação mais variada,
2.Aumentou a diversificação da produção (sem causa especifica para o aumento) para sustencia,
3.Aumentaram os alimentos variados disponíveis no mercado,
4.Diminuiram os alimentos variados disponíveis no mercado,
5.Outro, explique

60. Como mudou o acesso a alimentação saúdavel e nutritiva (ex: frutas e verduras) do seu domicílio, desde o começo de trabalho/gerencia dessa propriedade até hoje? (**se 3 pule para pergunta 62**)

1. muito mais baixa	2.um pouco mais baixa	3.mais ou menos a mesma	4.um pouco mais elevada	5. muito mais elevada

61. Qual foi a principal razão para a mudança de acesso á alimentação saudável e nutritiva?
____
____

1.Aumentou a renda a partir de nossa produção (sem causa específica para o aumento) com que pudemos comprar alimentação mais saudável/nutritiva,
2.Aumentou a produção de produtos saudáveis/nutritivos (sem causa especifica para o aumento) para sustencia,
3.Aumentaram os alimentos saudáveis/nutritivos disponíveis no mercado,

4.Diminuiram os alimentos saudáveis/nutritivos disponíveis no mercado,
5.Outro, explique

Parte E: Participação/benefício do programas rurais

Todos os empréstimos (incluindo PRONAF)

62. Você ou outro membro do domicílio fez algum **empréstimo** para **investir na agricultura** nesta propriedade entre o **começo** de seu trabalho/administração nessa propriedade **até hoje**? (Inclue empréstimos de bancos, PRONAF e empréstimos informais da família ou amigos)

PRONAF são aqueles emprestimos para os agricultores familiares com DAP, e ***pode ser*** *dada por por ejemplo Banco do Brasil e o programa "Mais Alimento"*

___1.sim, ___2.*não****, se não verifique que eles não tenham "acesso a nenhua fonte de financiamento, nem mesmo familia/amigos" e depois pule para Q65***

63. Qual foi a sua motivação principal para fazer empréstimo? (motivação, não uso)

____

Só exemplo para nós ver que tipo de resposta queremos, mas e importante escrever todos os detalhes de sua resposta
1. Investir na produção atual para aumentar a produção ou renda
2. Começar um novo tipo de produção com mercado mais rentável
3. Mudar o modo de produzir para adaptar a nova realidade com falta de mão de obra
4. Mudar o modo de produzir até um modo mais sustantável
5. Outro, explique

64. Para os empréstimos que você pegou, por favor dê detalhes sobre cada empréstimo e sua experiência com eles.

Ano	**De onde?** 1.PRONAF neste municipio, 2.PRONAF em outro municipio, 3.Banco comercial, 4.Grupo microcredito, 5.Familiares, 6.Agiota, 7.Outro, explique):	**Beneficiário** 1.Domicilio, 2.Cooperativa /associação, 3.Grupo de produtores (consorcio) 4.Outro, explique):	**Emprestimo coletivo, quantos domicílios pagaram**	**Total R$**	**Uso de emprestimo**	**No de parcelas de pagar total em meses (já pago ou estimado) ex: 12 = 1 ano**	**Já começou pagar o empréstimo?** 1.Sim, 2.Não	**Como foi o grau de dificultade para pagar?** 1.muito difícil, 2.difícil, 3.neutro, 4.fácil, 5.muito fácil

Se a pessoa tem um emprémstimo mais não de PRONAF, pule para pergunta 66
Se a pessoa tem um empréstimo de PRONAF, pule para pergunta 80/PAA

65. Qual foi a principal razão para nunca fazer um empréstimo?

____

____

1.Não foi capaz de realizar o processo de iscrição,
2. Ficou preocupado demais com o pagamento,
3. As taxas de juros são altas demais,
4.Não teve que fazer mudança que precisasse de emprestimo,
5. Outro, explique

66. Qual foi a principal razão para nunca fazer um empréstimo PRONAF?

____

____

1.Não foi capaz de realizar o processo de iscrição,
2. Ficou preocupado demais com o pagamento,
3. As taxas de juros são altas demais,
4.Não teve que fazer mudança que precisasse de emprestimo,
5. Outro, explique

<u>PAA/PNAE</u>

80. Você jã participou do programa PAA ou PNAE (merenda escolar), se sim em qual ano começou a particiapr?
____________ano, ___2.não, **se não pule para Pergunta 82**)

81. Em que município você participou ou participa do PAA/PNAE*?*
________________________*(em seguida, **pule para a Pergunta 83**)*

82. Se você nunca participou, quais foram as suas razões para não participar? *(**em seguida pule para a pergunta 111** (tem cuidado com o orden das perguntas – vai depois de Q93)*

____

83. Em quais anos você participou no PAA/PNAE? ___________________________(**todos os anos**)

84. Qual foi a principal razão para participar do PAA/PNAE?

____

____

1.Para acessar um mercado mais estável,
2.Para acessar um mercado adicional,
3.Para acessar um mercado com preço maior,
4.Outro, explique

85. Porque você não participa ou participou no PAA/PNAE antes? ____

1. Não tinha o PAA/PNAE no municipio antes
2. Não tinha conhecimento do PAA/PNAE,
3. Não tinha interés,
4. Queria participar antes mas não sabia como participar
5. Tentei participar mas não consegui ter um contrato
6. Outro, explique

86. Se você participou/participa de forma irregular, por que você não participou em algums anos? ____

1. Porque o programa não estava ativo naquilos anos
2. Porque não foi rentável naquilos anos
3. Quis participar mas não houve contratos suficientes
4. Outro, explique
99. Não se aplica porque participa regular

87. Por favor descreva os detalhes de participação de PAA e PNAE nos últimos 12 meses

Programa 1.PAA, 2.PNAE	**Participante** 1.Domicílio, 2.Cooperativa/associação, 3.Um consorcio de fazendeiros 4.Outro, explique:	**Produtos (todo que se aplica)** 1. Verduras 2.Legumes 3.Graos cereais 4.Carnes 5.Laticinios 6.Ovos 7.Bolo,doce 8Frutas	**Quando e para quais épocas foram os últimos pagamentos?** 1. Ago-Dec 2015 2. Fev-Ago 2016 3.Outro, explique	**Valor R$**	**Duração da viagem para ponto de entrega em minutos**

87.9 Como foi o processo de produzir para PAA/PNAE (em termos de quantidade suficiente para o tempo necesario)?
_____1.Muito difícil,_____2.Difícil, _____3.Neutro, _____4.Fácil, _____5.Muito facil

87.10 Como foi o processo de entregar para PAA/PNAE?
____1.Muito difícil, ____2.Difícil, ____3.Neutro, ____4.Fácil, ____5.Muito facil

87.11 Os produtos entregues para PAA/PNAE representam qual percentual (%) da sua venda total?__

90. Você consegue vender tudo que você gostaria para PAA/PNAE? ___1.sim, ___2.não

93. Pensa na produção da sua terra como um todo nos últimos 12 meses, quais são os 3 produtos mais rentáveis e quais são seus mercados principais?

Produto	**Área total para produção**	**Unidade** 1. metros quadrados 2.hectares 3.alqueires	**Produção total**	**Unidade** 1. quilos 2.litros 3.numero de animais ou cabeças 4.tonelada=1000kg 5.metros cubicos=1000litros 6.pes	**Mercado principal do produto** 1. PAAPNAE 2.Sacolao 3.Supermercado local 4.Ceasa 5.Ceagesp 6.Atravessadores 7.Prefeitura	**Proporção de venda total a esse mercado** (%)	**Duração da viagem para mercado no minutos**

				7.duzias 8.outras, explique:	8.Comercio local 9.Comercio da região 10. outro, explique		

<u>Bolsa Familia</u>

111. Algum membro do domicílio já recebeu dinheiro da Bolsa Famiília? ___1.sim,___2.não**, pule para Q114.7.1 se tem outras programas**

112. Em quais anos você participou do Bolsa Familia? ______________________(**todos os anos**)

113. Qual é o valor total recebido de Bolsa Familia nos últimos 12 meses? R$_________________

Q114.7.1 <u>Impacto dos programas no uso da tera</u>

1-7: **<u>Houve alguma mudança</u>** no uso de...**<u>por causa de</u>** emprestimo **<u>PRONAF</u>**, participação de **<u>PAA/PNAE</u>**, **<u>Bolsa Familia</u>**?

1. Diminuiu muito
2. Diminuiu um pouco
3. Não mudou
4. Aumentou um pouco
5. Aumentou muito

1.1-7.1: **<u>PRONAF</u>**: Essa mudança **<u>continuou</u>** nos anos seguintes **<u>até agora</u>**?

1. Sim
2. Não

1.1-7.1: **<u>Irregular PAA/Bolsa Familia</u>**: Essa mudança **<u>continuou</u>** nos anos de **<u>não participar</u>**?

1. Sim
2. Não

Programa	**1.Tamanho da terra**	1.1Cont?	**2.Insumos quimicos**	2.1Cont?	**3.Máquinas**	3.1Cont?	**4.Sementes**	4.1Cont?	**5.Produção variada**	5.1Cont?	**6.Tempo de produção**	6.1Cont?	**7.Produção total**	7.1Cont?
PRONAF														
PAA/PNAE														
Bolsa Familia														

<u>Mais PRONAF</u>

67.8. Houve alguma outra mudança qua ainda não falamos no uso da terra por causa do emprestimo PRONAF?
1. Sim, explique____, ____2.Não, **pule para 67.10 se nehuma mudança ou Q71 com**

67.81 Essa mudança continuou nos anos seguintes até agora? ____1.Sim,___2.Não

67.9. Houve alguma mudança mais que ainda não falamos no uso da terra por causa do emprestimo PRONAF?
1. Sim, explique____, ___2.Não, **pule para Q71**

67.91 Essa mudança continuou nos anos seguintes até agora? ___1.Sim,___2.Não, **pule para Q71**

67.10 O Sr(a) disse que não houve mudança no tamanho e nem uso da terra da sua propriedade por causa do emprestimo do PRONAF. Por que não houve mudança? ____,

71. Se você teve mais de um empréstimo, qual empréstimo do PRONAF teve o maior impacto no uso da terra de seu propriedade? ___________________(1. Primerio até 8. Oitavo, ou 9. Houve impacto igual)

Mais PAA/PNAE

99. 8. Houve alguma outra mudança no uso da terra por causa de participar no PAA/PNAE?
1. Sim, explique____
___2.Não, **pule para Q100 sim mudança anterior, Q101 se nehuma mudança,**

99.81 Se você participa/ou irregularmente, essa mudança continuou nos anos de não participar no PAA/PNAE? ____1.Sim,_____2.Não,

99. 9. Houve alguma mudança que ainda não falamos no uso da terra por causa de participação no PAA/PNAE?
1. Sim, explique____
____2.Não, **pule para Q100 sim mudança anterior, Q101 se nehuma mudança**

99.91 Se você participa/ou irregularmente, essa mudança continuou nos anos de não participar no PAA/PNAE? ____1.Sim,____2.Não

100. Qual foi a principal razção para PAA/PNAE impactar o uso da terra da sua propriedade? (pule para Q114.8 **se teve Bolsa Familia, Q117 se não**
____

101. O Sr(a) disse que não houve mudança no tamanho e nem uso da terra de sua propriedade por causa de seu participação de PAA/PNAE. Por que não houve mudança?
____
Pule para Q117 se não teve Bolsa Familia

Mais Bolsa Familia

114. 8. Houve alguma outra mudança no uso da terra por causa de participação no Bolsa Familia?
1. Sim, explique____
___2.Não, **pule para Q115 com mudança e Q116 sem mudança**

114.81 Essa mudança continuou nos anos sem Bolsa Familia?____1.Sim, explique,______2.Não

114. 9. Houve alguma mudança mais que ainda não falamos no uso da terra por causa de participar na Bolsa Familia?
1. Sim, explique____
_____2.Não, **pule para Q115**

114.91 Essa mudança continuou nos anos sem Bolsa Familia?____1.Sim,____2.Não, **pule para Q115**

115. Qual foi a razão principal para participação da Bolsa Familia o uso da terra da sua propriedade?
____

116. Porque a participação na Bolsa Familia não teve nenhum impacto no tamanho nem uso da terra na sua propriedade?

Q117-Q119 <u>Impacto dos programas no accesso ao alimentação</u>

117-119: **<u>Houve alguma mudança</u>** no uso de...**<u>por causa de</u>** emprestimo **<u>PRONAF</u>**, participação de **<u>PAA/PNAE</u>**, **<u>Bolsa Familia</u>**?

1. Diminuiu muito
2. Diminuiu um pouco
3. Não mudou
4. Aumentou um pouco
5. Aumentou muito

117.1-119.1: **<u>PRONAF</u>**: Essa mudança **<u>continuou</u>** nos anos seguintes **<u>até agora</u>**?

1. Sim
2. Não
   - se não: Como não continuou?

117.1-119.1: **<u>Irregular PAA/Bolsa Familia</u>**: Essa mudança **<u>continuou</u>** nos anos de **<u>não participar</u>**?

1. Sim
2. Não
   - se não: Como não continuou?

Programas	**Q117 Alimentação (em termos de quantidade)?**	Q117.1 Cont?	**Q118 Alimentação variada?**	Q118.1 Cont?	**Q119 Alimentação saudável e nutritiva (ex: frutas,verduras)**	Q119.1 Cont?
PRONAF						
PAA/PNAE						
Bolsa Familia						

PRONAF mudança = Q75
Nehum mudança PRONAF = Q76.a,
PAA com mudança Q105 ou PAA sem mudança Q106,
Bolsa Familia com mudança Q120 ou Bolsa Familia sem mudança Q121

75. Qual foi a principal razão para PRONAF impactar o acesso ao alimentação de seu domicilio?

    ____

    Se tem mais que um emprestimo pule para Q78, se não pule para PAA Q105 com/Q106 sim ou Bolsa Familia com Q120/sim Q121, ou Q122

76.a O Sr(a) disse que o emprestimo PRONAF não impactou o acesso ao alimentaçao do seu domicilio. Por que não impactou?

____

78. Qual empréstimo PRONAF teve o maior impacto no acesso ao alimento do seu domicilio?

____________1.Primeiro até 8.Oitavo, 9.Houve impacto igual

105. Qual foi a principal razão para participação do PAA/PNAE impactar o acesso de alimentação do seu domicilio? **(pule Q120 com mudança Bolsa Familia, Q121 sem mudança, ou Q122 sem)**

____

106. Porque a participação no PAA/PNAE não impactou o acesso ao alimentação do seu domicilio? (**pule Q121 com Bolsa Familia sem mudança**)

____

120. Qual foi a razão principal para participação do Bolsa Familia impactar o acesso de alimentos do seu domicilio? **(depois pule para Q122)**

____

121. Porque a participação no Bolsa Familia não teve nenhum impacto no acesso de alimentação do seu domicilio?

Parte F: Produção agrícola e Renda do domicílio (nos últimos 12 meses)

Agora vamos falar um pouco sobre sua renda e produção. Mas uma vez reforçamos que os dados da pesquisa são sigilosos, então por favor não tem medo de falar verdadeira.

122. Quanto seu domicílio recebeu nos últimos 12 meses (R$) de outros programas governmentais não mencionadas? (por exemplo PET, BPC, Aposentadoria, renda idoso etc.)
R$ _____________

124. Quanto (R$) seu domicilio recebeu da produção da propriedade, incluindo aluguel de terra, durante os últimos 12 meses? *(também inclue renda de produção de outro municipio)*
R$___________________

125. Qual foi a rendamento total (R$) do seu domicilio nos últimos 12 meses?_________R$

126. Quanto dinheiro seu domicílio gastou com os seguintes itens agrícolas nos últimos 12 meses, e qual quantidade?

Categoria	**Sim**	**Custo (R$)**	**Quantidade**	**Unidade** 1. quilos 2.litros 4tonelada=1000kg 5metros ubicos=1000litros 6.arrouba=15kg 7. horas máquina 8. numero de máquinas	**Número de aplicação em 12 ultimos 12 meses (días para máquinas e trabalho contratado)**
Insumos químicos: adubo					
Insumos químicos (veneno): pesticidas					
Insumos químicos (veneno): herbicidas					
Insumos químicos (veneno): fungicida					
Insumos agrícolas não químicos (esterco, resíduo, etc)					
Material de plantio (sementes, mudas, plantas agrícolas)					
Irrigação					
Força de tração e máquinas contratadas durante preparação, cultivo e colheita				_____no maquinas	_____________dias
Forragem animal					
Custos veterinários					
Animais fixos					
Transporte de produtos, ex petróleo					
Trabalho contratado				______no pessoas	___________días
Pagamento de aluguel de terras					
Pagamento por compra de terras					
Pagamento do PRONAF/outros empréstimos agrícolas					
Other, specify/outro, explique:					
Other, specify/outro, explique:					

Produção e gestão agrícola

127. Nos últimos 12 meses quanto da sua produção agrícola e pecuária total foi para as seguintes fontes?
1.Troca_____________%
2.Doação___________%
3. Subsistencia_______%
4. Mercado (venda)______%

129. Vamos falar sobre tipos de alimentação que seu domicilio produciou e consumiu nos últimos 12 meses.

Produto	**Qual proporção (%) da produção foi vendida**	**Qual proporção (%) da produção foi consumido pelo domicílio**	**Qual proporção (%) do consumo total veio de produção própria**
Frutas			
Vegetais			
Cereais			
Produtos animais			

131. Quais são os **produtos florestais** dentro ou fora da propriedade, que colheram nos últimos 12 meses? (por exmplo lenha, madeira, carvão, carne ou fruta fora da propriadade

Produto	**De ónde** 1. Dentro da propriedade 2. Fora da propriedade	Qual proporção (%) da colheita foi para uso do domicilio/propriedade?	Qual proporção (%) da colheita foi para outros usos fora do domicilio (ex: venda ou doação)?

Se teve PAA/PNAE pule para Q136

132. Nos últimos 12 meses quais são os 3 produtos mais rentáveis e seu mercado principal?

Produto	**Área total para produção**	**Unidade** 1. metros quadrados 2.hectares 3.alqueires 4.ares	**Produção total**	**Unidade** 1. quilos 2.litros 3.numero de animais ou cabeças 4.tonelada=1000kg 5.metros cubicos=1000litros 6.pes 7.duzias 8.outras	**Mercado principal do produto** 1. PAAPNAE 2.Sacolao 3.Supermercado local 4.Ceasa 5.Ceagesp 6.Atravessadores 7.Prefeitura 8.Comercio local 9.Comercio da região 10. outro, xplique	**Proporção de venda total a esse mercado** (%)	**Duração da viagem para mercado no minutos**

136. Quanta formação agrícola seu domicilio como um todo tem? (você e os outros membros)

___1.Nenhuma,_____2.Um pouco (1-2 dias),_____3.Alguma,______4.Varias,_______5.Muita

140. Quais leis influenciam (ex: limitam ou facilitam) a administração/uso da terra/propriedade e como eles influenciam suas decisões?

Lei	**Decisões influenciadas**

Condições bio-físicas da propriedade (nos últimos 12 meses)

141. Nos últimos 12 meses aconteceu alguma coisa especial que afetou a sua produção agrícola? *(Ex: erosão, fertilidade, clima, polinização, doença dos humanos, animais ou plantas)*

____

____

142. Existem algumas carateristicas específicas na sua propriedade que contribui positivamente ou negativamente na sua produção?

Caraterísticas positivas	**Caraterísticas negativas**

143. O Sr(a) tem a expectativa de que algum membro do domicilio vai sucede-lo nas atividades da propriedade?______1.Sim,______2,Não

Muito obrigada por participar da nossa pesquisa. Eu gostaria de reforçar mais uma vez que todas as informações que você forneceu são confidenciais. Os dados da pesquisa serão anônimos e serão utilizados exclusivamente para propósitos de pesquisa com o objetivo de ver as condições dos agricultores familiares e como melhorar os meios de subsistência da região da Mata Atlántica e do Cerrado. Se entrarnos em contato com você num tempo atrás com uma pesquisa de acompanhamento, gostaríamos muito que pudesse responder, mas não existe nenhuma obrigação em fazer isso.

Tempo ao final (XX:XX):________________________