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Ludovic Bequet

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Abstract

This paper presents the first detailed empirical evaluation of the effect of agricultural productivity on land inequality using the context of genetically modified (GM) corn seeds introduction in the Philippines. Using three waves of census data covering 21 years and 17 million plots, I identify the effect by exploiting exogenous variations in soil and weather, leading to differences in potential gain from GM corn cultivation. Results show that municipalities that benefited more from the technology experienced an increase in landholding inequality, measured by the area farmed by top decile and by the Gini index. This effect is partly driven by a relative increase in agricultural land and more precisely by a lower contraction in more affected areas. While increased land inequality is associated with a higher level of terrorist activity, it does not seem to have any adverse effect on poverty, household income or expenditure.

***JEL* Classification: O13, Q12, Q14, Q15**
Keywords: Land inequality, Agricultural technology, Land reform

*University of Namur, CRED, Remparts de la Vierge 8, 5000 Namur; e-mail: ludovic.bequet@unamur.be
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1 Introduction

The structure of a country's agricultural sector is strongly linked to its development level. In low-income countries, it is characterized by a large number of smallholder farmers while in high-income countries, farms tend to be larger and fewer[1]. This difference can be explained by the process of structural transformation, whereby workers move out of agriculture into the industrial and the service sectors. This implies a substantial reallocation of agricultural land between those who leave and those who stay. How this reallocation takes place shapes the land distribution, which has implications for the distribution of income and wealth at the national level.

Gains in agricultural productivity have been identified as a key driver of this structural transformation as they reduce the demand for agricultural labor and increase the demand for manufacturing goods. While there has been an extensive literature studying the impact of agricultural productivity on land expansion (see Villoria et al. (2014) for a review), its effect on land inequality has so far remained unaddressed. This is striking given that modern agricultural technologies are often blamed for favoring large farms, at the expense of smallholder farmers, leading to an increase in land concentration. These claims are especially common for genetically modified (GM) crops but are rarely backed by data or only based on very loose empirical analysis (Catacora-Vargas et al., 2012; Phélinas and Choumert, 2017). Herbicide tolerance and pest resistance - the two main traits in GM crops - are labor saving as they decrease the need of manual weeding and pesticide spraying respectively. As Bustos et al. (2016) show, this kind of labor-augmenting technology can drive structural transformation and is therefore likely to lead to a redistribution of agricultural land. Moreover, the higher return on capital is likely to favor better-off farmers and lead to higher levels of inequality.

This paper presents the first empirical evaluation of the effect of agricultural productivity on land inequality, focusing on the two decades surrounding the introduction of GM corn seeds in the Philippines. Corn is the second most-cultivated crop in the country, mostly by smallholder farmers who rank among the poorest categories of the population (Reyes et al., 2012). GM seeds were introduced in 2003, rapidly adopted by the farmers and can be considered as the most important technical innovation for corn agriculture in the recent decades.

The economic literature on land distribution usually studies the *impacts* of land inequality rather than its drivers. The most compelling argument for a more equal land distribution comes from a series of papers, starting with Alesina and Rodrik (1994), showing a negative correlation between inequality - especially land inequality - and economic growth[2]. Historical evidence suggests that this is driven by lower investment in physical and human capital in areas with unequal land distribution[3]. Likewise, land redistribution policies have been shown to decrease poverty in India (Besley and Burgess, 2000),

[1] Using agricultural census data from 92 countries, Lowder et al. (2016) find that farms smaller than 2 ha account for 30-40% of land in low- and lower-middle-income countries and less than 10% in upper-middle- and high-income countries.

[2] See also Easterly (2007); Fort (2007), Neves et al. (2016) and Cipollina et al. (2018) for meta-analyses

[3] Banerjee and Iyer (2005); Baten and Hippe (2018); Cinnirella and Hornung (2016); Galor et al. (2009)

South Africa (Keswell and Carter, 2014) and the Philippines (Reyes, 2002; World Bank, 2009). This may be due to the fact that a more equal distribution generates more employment per hectare (and per unit of output) as small sized farms are more labor intensive and access to land provides a safety net which may encourage non-farm business investment (Binswanger-Mhkize et al., 2009). Furthermore, as agricultural activity in developing countries exhibits diseconomies of scale - the so-called "inverse farm size-productivity" -, redistributing land to smallholder farmers may lead to efficiency gains. This is supported by Vollrath (2007) who finds a negative relationship between land Gini and agricultural productivity using cross-country data. However, this claim has recently been challenged by Foster and Rosenzweig (2017) who show with micro-data that the relationship between farm productivity and size is in fact U-shaped and that large farms are as efficient as small ones, even in developing countries[4].

Land inequality has also been linked with an increased likelihood of conflict (de Luca and Sekeris, 2012; Peters, 2004; Thomson, 2016), environmental degradation (Ceddia, 2019; Sant'Anna, 2016) and reduced resilience against natural disasters (Anbarci et al., 2005)[5]. Despite this large number of studies on the – mostly negative – effects of land inequality, there exists surprisingly little research on its drivers. One notable exception is Bardhan et al. (2014) who use rich panel data from West Bengal to show that household division is a much larger driver of land distribution than land market transactions or the land reform. At a more aggregate level, Lowder et al. (2016) and Jayne et al. (2016) also provide a detailed description of agricultural land distribution, respectively for the whole world and in four African countries. The question of the distributional impacts of agricultural technology is however not new in economics and echoes an old literature studying the distributive effects of the Green Revolution, especially in South Asia[6]. These papers relied on very limited data sources, usually from a few hundred households. Moreover, they only focused on describing the change in inequality and did not rely on causal identification strategies. The present work therefore addresses an old question using modern empirical tools. It is also linked to the literature on agricultural productivity and structural transformation, in particular Bustos et al. (2016)[7] and can be seen as a description of the land redistribution process resulting from a more structural change of the economy.

To document the landholding inequality in the Philippines during the decades surrounding the introduction of GM corn in 2003, I use three waves of census data covering 21 years and 17 million plots. First, I show that landholding inequality increased between 2002 and 2012, despite an ongoing land reform aimed at redistributing agricultural land. A Theil's inequality decomposition reveals that within-municipality inequality accounts for 80% of total inequality. Changes in national inequality are therefore highly likely to be driven by changes at the local level and the rest of the empirical analysis

[4]Similarly, Adamopoulos and Restuccia (2019) find that land redistribution during the agrarian reform in the Philippines led to a 17% decrease in productivity.

[5]See also Guereña and Wegerif (2019) for a recent multi-disciplinary review.

[6]Bardhan (1974); Chaudhry (1982); Freebairn (1995); Otsuka et al. (1992); Prahladachar (1983); Raju (1976)

[7]Note that, while the new corn variety described in Bustos et al. (2016) is a land-augmenting technology, the introduction of GM corn in the Philippines was likely labor-augmenting and is more comparable to that of GM soy in their paper.

takes the municipality as unit of observation[8]. This gives a large enough number of observations to use traditional empirical methods.

As the census data does not distinguish between GM and non-GM corn, it is not possible to correlate the use of the technology with land inequality measures. Moreover, such an empirical strategy would be subject to reverse-causality bias. Indeed, it is not clear whether a positive correlation would mean that higher adoption rates lead to higher land concentration or simply that the technology is adopted in places where land is less equally distributed. To overcome this identification issue, I take advantage of exogenous variations through space and time. First, I compare data collected in 2002 – one year before GM seeds were commercialized – with data from 2012, in a first-difference setting, similar to a municipality fixed effects model. Second, I exploit differences in local soil and weather characteristics to compute an exogenous variation in profitability from GM corn, an approach taken from Bustos et al. (2016)[9]. This allows to compare the change in land inequality between municipalities that benefited substantially from the technology and those that could only benefit marginally. Results show that landholding inequality increased in more impacted municipalities, an effect driven by an increase in the land share of the top decile. This effect can be partially explained by the fact that agricultural land is less likely to decrease in more affected municipalities and that inequality is positively correlated with agricultural area. In addition, heterogeneity analysis reveals some interesting effects. First, it is stronger in municipalities that adopted modern inputs later, i.e. where the potential for yield increase was higher. Second, it is larger in places with more credit penetration ten years before the seeds commercialization. This brings support to claims made by advocacy groups who identify the agricultural financing system as an important mechanism driving land concentration. According to anecdotal evidence, the high input costs associated with the new technology pushes farmers to take usurious loans from informal moneylender, with interest rates as high as 10-15 percent per month. In case of default, they become bankrupt and need to pawn or sell their land, usually to the financier, thereby increasing land concentration (Masipag, 2013). I am however unable to disentangle this effect from a more direct effect of credit availability on treatment intensity as adoption is likely to be higher in places with more financial services. I also find some geographical heterogeneity, with a stronger effect on the southern island of Mindanao. Finally, looking at land *ownership* inequality instead of landholding inequality reveals that this measure follows a similar pattern, although its measurement is more problematic because of data limitation.

[8] Agricultural censuses are the most commonly-used data source to investigate land inequality, going back to Deininger and Squire (1998). In a recent paper however, Bauluz et al. (2020) have advocated for the use of household surveys instead. They show that, while both data sources give comparable land Gini coefficients, adjusting for the landless population and the land value – both absent from census data – leads to important changes in inequality measures. While agricultural censuses do have shortcomings, they also offer the extensive coverage needed for the kind of analysis carried out in this paper. Indeed, computing land inequality indicators at the local level (municipality or even village) using household surveys would be highly imprecise given the low number of households typically surveyed in each location. Moreover, household surveys only take into account household farms and therefore systematically miss company-owned farms which tend to be larger. As an extreme example, Lowder et al. (2016) show that in Guatemala, the 2% largest farms from the agricultural census, representing 57% of total land, are absent from the LSMS household survey.

[9] Similar estimation strategies has been used in other related papers such as Dias et al. (2019); Moscona (2019)

To assess to robustness of the results, a series of tests are presented. First, I show that they are unaffected when controlling for the change in population size and composition, thereby ruling out migration as a mechanism. Second, controlling for additional topographical and geographical characteristics does not have a substantial impact on the results. Third, comparing 1991 and 2002 data fails to find a similar effect, showing that, municipalities that benefited more from the technology were not on a different trend. Previous productivity gains therefore did not have the same impact on landholding inequality. Fourth, the results remain significant when spatial correlation is taken into account using Conley standard errors and when standard errors are clustered at the provincial level. Fifth, I run the analysis at the level of the barangay (village) and find the same effect, especially when the sample is restricted to rural areas. Finally, using alternative definition of the treatment variable leads to similar results.

Given the literature showing that GM crops improve farmers' income on the one hand (Qaim, 2016), and the other literature documenting the adverse effects of land inequality on the other, the net effect of the technology appears uncertain, although the inequality effect is unlikely to offset all the productivity gain. In the last part of the paper, I investigate the correlation between land inequality and three sets of downstream outcomes: municipality-level poverty rate; income and expenditure data from household surveys and terrorist activity. Results point to a negative correlation between inequality and poverty but they are not robust to the inclusion of fixed effects and time-varying controls. On the other hand, terrorist activities measured as the number of attacks and the number of casualties are positively correlated with land inequality, especially the attacks perpetrated by communist groups. This suggests that the welfare costs of higher inequality are low on average, but may increase in less politically stable regions. These results however, need to be interpreted with caution as this last section lacks a proper identification strategy and is therefore subject to reverse causality and omitted variable bias.

2 Background

The Philippines is an archipelago composed of 7,641 islands, situated in South-East Asia with a total land area of 300,000 square kilometers. During the period analyzed in this paper, 1991-2012, it was considered as a lower-middle income country, with a share of employment in agriculture declining from 45% to 32% (World Bank, 2019). Despite sustained economic growth and a strong decline in overall poverty, poverty incidence remained high in rural areas, as 57% of agricultural households were characterized as poor in 2009, three times the proportion of non-agricultural households (Reyes et al., 2012). The country is also characterized by a high level of income, wealth and land inequality, owing to the legacy of Spanish colonialism which constituted a landed elite class occupying prominent positions in the country political and economic apparatus. This high level of inequality is at the root of the civil conflicts that have beset the country in the past decades, among which the Moro insurgency on the island of Mindanao (McDoom et al., 2019).

In an effort to address the issue of land inequality, the country has undergone a series of land reforms since the beginning of the twentieth century. The most recent one, the Comprehensive Agrarian Reform Program (CARP), started in 1988 with a triple objective of equity/social justice, farm efficiency and poverty reduction. The scope of this reform was extensive as it covered all agricultural land with a few exceptions[10]. Both tenants and regular farm workers were included as recipients, as long as they were landless or smallholder farmers (with less than 3 ha of land). The reform put an upper limit on ownership of agricultural land at 5 ha, plus 3 ha per heir of minimum 15 years at the time of the reform, provided that they were willing to continue tilling or managing the farm. Thirty years after the start of the implementation, the CARP claims to have redistributed 4.8 million hectares to 2.8 million households (Ballesteros et al., 2017). These figures however appear unrealistically high[11]. In addition, several scholars have criticized the reform implementation process for being captured by the landed elite and resulting in little distribution of wealth and power to the landless and smallholder farmers (Borras, 2006; Borras et al., 2007; Lanzona, 2019).

Corn is the second most-cultivated crop in the country. It is used both for consumption and sold to the booming animal feeds industry. In 2003, the country approved the commercialization of GM corn seeds. Farmers were fast to adopt this new technology and, by 2014, 62% of the hectarage devoted to corn was planted with GM seeds (ISAAA, 2017). The first generation of biotech corn included the *Bacillus thuringiensis* (Bt) trait, which confers the plant pest tolerance. In 2005, new varieties were commercialized exhibiting herbicide tolerance (Ht) as well. By 2012, the overwhelming majority of GM corn planted in the Philippines had both traits (Bt/Ht)(Aldemita et al., 2014). In addition to the patented GM seeds, illegal open-pollinated varieties (OPVs) containing herbicide-tolerant traits have been reported in the South of the country. These varieties, locally known as *sige-sige* are the result of cross-breeding between traditional cultivars and GM corn seeds. Using qualitative information, De Jonge et al. (2021) estimates that these varieties appeared in Southern Mindanao between 2005 and 2010 and nowadays account for 35 to 50% of maize farm land in Mindanao and the Visayas[12].

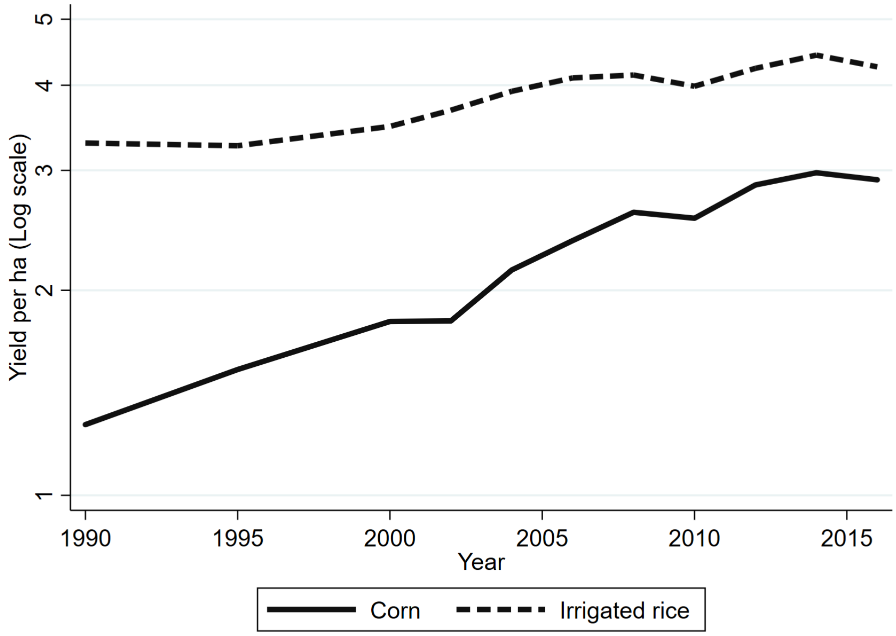
Figure 1 shows the evolution of corn and rice yields per hectare between 1990 and 2016, using official data from the Department of Agriculture. In the decade following the introduction of GM corn, corn yield almost doubled. Such a large gain in productivity was not observed in rice, the main crop of the Philippines. In line with the global literature on GM crops (Qaim, 2016), two papers have shown that GM corn has been beneficial to Filipino farmers. Yorobe and Smale (2012) use an instrumental variable strategy to account for adoption and find that it increased net farm income by USD 105 per hectare and monthly off-farm income by USD 49 through a reduction in labor requirements, highlighting the labor-saving effect of the technology. Heterogeneous effects estimated by Mutuc et al. (2013) with

[10] Exceptions include military reservations, penal colonies, educational and research fields, timberlands, undeveloped hills with 18 degrees slope and church areas.

[11] Indeed, according to the agricultural census, there were 3.76 million farmers in the Philippines in 1991 and when we add up the land area under leasehold and tenancy with the area owned in excess of 5 ha, we only reach 4.1 million ha. If the redistribution numbers are true, we would therefore observe a much larger decrease in land inequality than what is found in the subsequent censuses.

[12] Very little is known about the exact characteristics, origin and spread of this *sige-sige* corn. These figures are in line with those found by Bequet (2020) in a case study in Northern Mindanao.

Figure 1: Temporal evolution of corn and rice yield



Source: Bureau of Agricultural Statistics (2005, 2008, 2013); Philippine Statistics Authority (2018)

propensity score matching show that the farmers benefiting the most are smaller, poorer and less likely to adopt the technology.

3 Data

3.1 Agricultural census

3.1.1 Data harmonization

The evolution of landholding inequality is computed using the latest three waves of the Census of Agriculture and Fisheries (CAF), collected in 1991, 2002 and 2012 by the Philippine Statistical Agency (PSA), under the supervision of the FAO's World Census of Agriculture. This data provides plot-level information including size, tenure status, main use and the crops cultivated over the past year. Harvest and input information are unfortunately unavailable except for some very coarse measures of input use in 1991. Small differences in the sampling method, farm definition and the type of data collected warrants caution when comparing the three waves. In what follows, I briefly explain the two most important differences and how they are addressed. A more detailed description of the data cleaning process can be found in Appendix A.

Farms are defined at the level of the household and in the rest of the paper, farms and farming households are used interchangeably[13]. All farms with a total land area below 0.1 ha are removed from the analysis, a cutoff used in the 2002 census. This ensures that the temporal variations we find in the land distribution are not the result of changing farm definitions and that the households considered devote a significant amount of resources to their farming activity.

The first major difference between CAF waves is that only the last one provides a complete enumeration of all the farms in the country. In 1991 and 2002, a sample of barangays was drawn within each municipality. All farming households living in the sampled barangays were then enumerated. Sampling weights allow the computation of municipality-level statistics and are used in all the empirical analysis.

Another difference between CAF waves is that the location of the plot is reported at the barangay level in 1991 and 2012 and only at the larger, municipality level in 2002. This information is important as we are interested in the distribution of agricultural land, which needs to be computed over a given geographic area. As plots are usually located within walking distance from the place of living, we could run the analysis based on the residence. However, this approach is problematic for two reasons. First, when we speak of land distribution, we are intuitively refering of the distribution of the land located in the area of study, not of the land farmed by households living in that area. Second, farms cultivated by people living far from their plots or extending beyond administrative boundaries, are likely to be systematically different from the others. For example, agricultural land distribution in urban areas is not a relevant issue, whereas absentee landlords living in urban areas may have a non-trivial effect on the land distribution where their farms are located. For this reason, land distribution measures are computed based on the physical location of the plot and not on the residence of its operator. This analysis is carried out at the municipality level as this is the lowest level reported in the three waves[14].

The CAF also reports the land tenure status of each plot, which I divide between ownership (full ownership, owner-like possession and various forms of community ownership) and tenancy (rental, leasehold, rent free occupation). When the farmer is a tenant, we do not have any information regarding the owner of the plot. Indicators of land inequality therefore measure *landholding* inequality and not land *ownership* inequality[15].

3.1.2 Land distribution across farms

The distribution of agricultural landholdings in the Philippines is described in Table 1. The total land devoted to agriculture increased over the first decade from 8.6 to 9.6 million ha and then strongly

[13] This implies that several operators working independently from each other but living together (e.g. a father and a son) are considered as one farming unit.

[14] In addition, the incompleteness of the CAF1991 prevents from computing barangay-level statistics based on plot location. Indeed, we systematically miss the information from households living in non-sample barangays. For non-sample barangays, this means that we only have information on the land cultivated by outsiders. In sampled barangays, we potentially miss many of the outsiders. As farms spreading over administrative boundaries are likely to differ systematically from the others, this would create biases in our land distribution measures. Taking the plot municipality instead solves this problem as all municipalities are enumerated.

[15] As noted by Vollrath (2007), landholding inequality matters for efficiency while land ownership inequality is more relevant from an equity perspective

decreased in the second decade to 7.5 million ha. This pattern is driven by a strong increase in farm number between 1991 and 2002 and a steady decrease in average farm size over the whole period, which was probably driven by the land reform. In addition, total population strongly increased over the period, from 60 to 92 million inhabitants, while the share of rural population remained relatively constant, around 50%. This strong demographic expansion increased the pressure on land and may also explain part of the decline in farm area.

Table 1: Summary statistics of national land distribution

	1991	2002	2012
Agricultural area (million ha)	8.57	9.56	7.56
Number of farms	3.76 million	4.8 million	4.55 million
Average farm size (ha)	2.28	1.99	1.64
Landholding Gini	0.590	0.576	0.606
Share top 1%	18.73%	15.34%	19.68%
Share top 10%	46.85%	44.86%	48.02%
Share bottom 50%	13.10%	13.74%	12.32%
Share tenanted land	34.07%	31.19%	27.80%
Share tenanted farms	31.01%	25.30%	25.75%
Population (million)[a]	60.703	75.698	92.100
Share of rural population[a]	51.3%	48.9%	50.9%

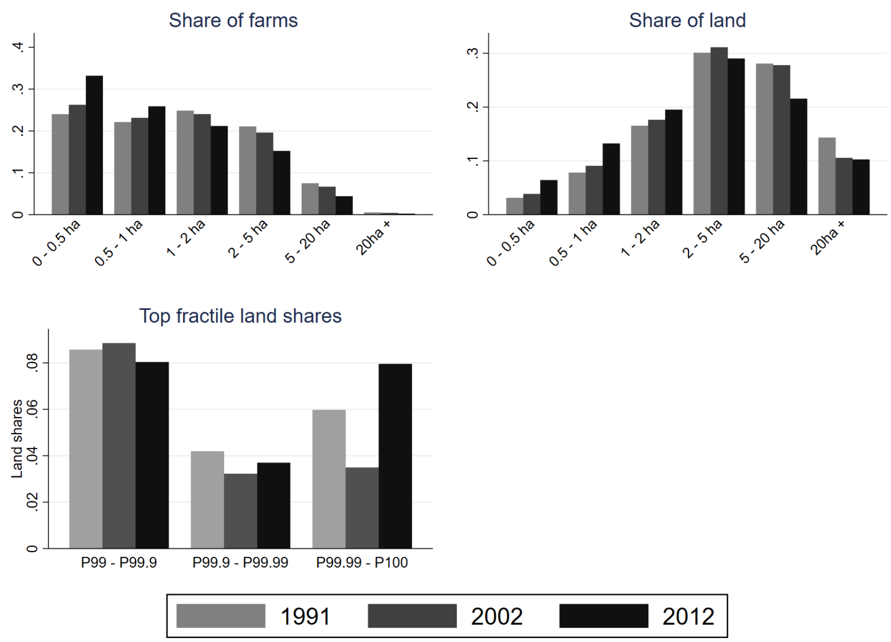
[a] Figures from the Population Censuses of 1990, 2000 and 2010.

Land inequality measures also exhibit a non-linear pattern, decreasing in the first decade and then increasing to levels higher than in 1991. The Gini coefficient – the most commonly-used inequality indicator – is 0.606 in 2012, up from 0.590 in 1991 and 0.576 in 2002. Such levels are high for the ASEAN region but remains below those recorded in Latin American countries (Guereña, 2016). The share of land occupied by different fractiles, shows a very similar pattern of decreasing inequality between 1991 and 2002 which is reversed between 2002 and 2012. At the end of the period, farms in the top percentile (decile) control almost 20% (50%) of the land, a share that has increased by more than 4 pp (3pp) since 2002. At the other end of the distribution, the 50% smallest farms occupy 12.3%, down from 13.74% in 2002.

To illustrate the changes in the landholding distribution, Figure 2 presents the temporal evolution in the number of farms and total farm area by land size category. Over time, the share of small farms (< 1ha) increases while the share of farms above 1 ha decreases. The share of land occupied by each category follows a similar pattern except that the decrease only starts after 2 ha. This may be due to the land reform which redistributed land to smallholders.

In the right tail of the distribution, the share of land occupied by farms above 20 ha remains stable between 2002 and 2012, despite a steady decrease in their numbers (from 0.38% of farms in 2002 to 0.21% in 2012), which indicates an increase in the size of very large farms. This is confirmed by the last graph which shows the share of land by fractile at the top of the distribution. While it remains

Figure 2: Farm size and land share distribution



relatively stable up to P99.99, the last 0.01% more than doubles its share between 2002 and 2012.

Finally, the share of tenanted land decreases steadily over the two decades while the share of tenanted farms declines sharply between 1991 and 2002 and then remains stable around 25%. This indicates that land ownership inequality exhibit a different pattern than landholding inequality.

3.1.3 Inequality decomposition and municipality-level land inequality

Since land is an immobile asset, it is expected that most of the inequality is to be found at the very local level. Intuitively, farmers need to live close to their farms either because they work in them or because they need to be able to monitor their workers. It is therefore not possible for large farmers to concentrate in specific areas in the same way that wealthy individuals live in the same neighborhoods. In the following, I compute the share of total inequality that can be attributed to within-municipality inequality, using the General Entropy (GE) index (also known as Theil's index - see Appendix B for the technical details of the decomposition).

As expected, the results of this decompositions reported in Table 2 show that within-municipality inequality accounts for a very large share, around 80%, of total land inequality. The remaining between-municipality component comes from two sources. First, from differences in area and population density, which might reflect differences in soil fertility as small farms are only likely to be profitable in productive areas. Second, from farms occupying land across municipal boundaries. Indeed, if a farm is located on two municipalities, it will counted as one farm in the national measure but will be split into two in the municipal measure. How land distribution evolves at the local level therefore appears as an important contributor to national land inequality dynamics.

Table 2: Landholding inequality decomposition

		1991	2002	2012
Theil's T	Total	0.996	0.804	1.134
	Within municipality	0.785	0.686	0.953
		78.81%	85.32%	84.04%
	Within barangay			0.761
				67.11%
Theil's L	Total	0.672	0.636	0.727
	Within municipality	0.526	0.523	0.588
		78.27%	82.23%	80.88 %
	Within barangay			0.514
				70.70%

Table 3: Summary statistics of municipality-level landholding distribution

		(1) 1991		(2) 2002		(3) 2012
Variable	N	Mean/SD	N	Mean/SD	N	Mean/SD
Total land area	1418	5690.422	1552	5926.297	1545	4828.659
		(6380.557)		(6102.793)		(5580.705)
Nb of farms	1418	2593.834	1552	3051.139	1545	3033.344
		(2153.945)		(2509.451)		(2728.821)
Gini	1418	51.256	1552	51.848	1545	52.285
		(9.689)		(8.933)		(9.971)
Share top 1%	1418	13.648	1552	12.901	1545	12.710
		(11.747)		(9.666)		(11.246)
Share top 10%	1418	40.004	1552	40.239	1545	40.239
		(10.918)		(9.423)		(10.542)
Share bottom 50%	1418	16.752	1552	16.395	1545	16.010
		(4.670)		(4.490)		(5.116)
Share tenanted land	1418	35.640	1552	34.154	1545	31.427
		(16.025)		(15.860)		(16.168)
Share tenanted farms	1418	28.810	1552	24.794	1545	26.564
		(16.126)		(14.979)		(15.008)

Most of the empirical analysis of this paper focuses on the difference in municipality-level inequality between 2002 and 2012. In order to ensure that any difference we find is not driven by the sample composition, I restrict the 2012 data to the barangays enumerated in 2002 when computing municipality-level indicators. In addition, municipalities with less than 50 ha of agricultural land are dropped from the analysis. This restricts the sample to areas where farming is of some importance. Metropolitan Manila (National Capital Region) is also excluded from the analysis, as it is mostly urban. This sample restriction alleviates the issue of outliers driving our results and are applied throughout the rest of the empirical analysis. Table 3 reports the descriptive statistics of municipality-level land distribution. Total land area and the number of farms follow similar a pattern on average as at the national level. The inequality measures, on the other hand, behave differently, as the Land Gini increases steadily over time, while it decreased at the national level during the first decade. More surprisingly, the average top 1% share decreases over time and the top 10% share remains remarkably stable. This suggests that the increase at the national level was driven by relatively larger municipalities.

Maps of municipality-level Land Gini for the three waves of data are reported in Appendix C. Spatial correlation appears relatively limited, except for some regions characterized by strong land inequality such as the island of Negros in 1991 and central Mindanao in 2012. Temporal persistence, on the other hand, is high as unequal regions in 1991 tend to be more unequal in 2002 and 2012. The increase in land inequality over time is reflected by the darker colors in 2012.

3.2 Additional data sources

Aside from the CAF data, the analysis presented in this paper relies on additional data sources. First, the Census of Population (CP), available for the years 2000 and 2010, gives the municipality population and allows me to compute the share of rural population and the share of farming households. Second, GIS data from various sources is used to complement farm- and household-level data.

- Crop suitability measures come from the FAO Global Agro-Ecological Zones (GAEZ) database, which predicts yields for each crop based on soil, climate conditions and agricultural practices at a resolution of 10km per pixel. This measure will be further detailed in the section presenting the empirical strategy[16].
- Net Primary Productivity, obtained from NASA Earth Observatory (NEO), shows the difference between the carbon dioxide taken in by plants through photosynthesis and that released through respiration and is used as a proxy for vegetation growth[17].
- Geophysical measures such as altitude and ruggedness are computed thanks to the Space Shuttle Radar Topography Mission (SRTM) digital elevation model, which has a pixel size of 90m.
- Tree cover in 2000 and 2010 is obtained from the Hansen et al. (2013) global data which provides the tree cover share for each 30-m pixel.
- Night lights data come from the Defense Meteorological Program Operational Line-Scan System (DMSP-OLS), with a pixel size of 1km.

Each administrative area in the Philippines is uniquely identified by a Philippine Standard Geographic

[16] The data used in the analysis comes from the v3 of the GAEZ.

[17] It is available at a monthly frequency since 2000 with a pixel size of 10km. Due to strong seasonal variation in the measure, I take the average over the three years surrounding the CAF data collection (2001-2003 for CAF 2002 and 2011-2013 for CAF 2012)

Codes (PSGC). These codes are used to match the different waves of CAF and CP data over time and with GIS data, using administrative boundaries shapefiles, obtained from the UN Office for the Coordination of Humanitarian Affairs (OCHA). Manual matching by names was carried out in order to increase the quality of the match[18]. Finally, the last part of the paper uses additional data on poverty, income, employment and terrorist activity, which is presented in the relevant sections.

4 Identification strategy

This paper focuses on the period following the introduction of genetically modified corn in the Philippines, which took place in 2003. We therefore have a first census conducted twelve years before (CAF 1991), another one conducted one year before (CAF 2002) and the last one ten years later (CAF 2012). The main empirical analysis compares the two latest censuses, while using the first one to control for historical differences that may be correlated with the treatment.

Because the data does not distinguish between different corn varieties, we do not directly observe GM corn adoption. It is therefore not possible to look at the direct impact of adoption on land use and distribution, regardless of the endogeneity of technology adoption. To overcome this issue, I use the empirical strategy developed by Bustos et al. (2016) in their paper on structural transformation in Brazil. This strategy exploits the fact that differences in soil and weather characteristics lead to differences in potential gain from adopting the technology, thereby creating exogenous cross-sectional variation in adoption and in treatment intensity. The measure of this exogenous potential gain from GM crop cultivation is obtained from the FAO GAEZ database, which predicts yields for each crop based on soil, climate conditions and agricultural practices. Crucially for our strategy, those agricultural practices include various degrees of input level intensity. The low level of inputs implies that "*the farming system is largely subsistence based. Production is based on the use of traditional cultivars (...), labour intensive techniques, and no application of nutrients, no use of chemicals for pest and disease control and minimum conservation measures*". The high input level implies that "*[c]ommercial production is a management objective. Production is based on improved or high yielding varieties, is fully mechanized with low labour intensity and uses optimum applications of nutrients and chemical pest, disease and weed control*". The difference in potential yield between high and low levels of inputs therefore serves as a proxy for the profitability gain from improved agricultural technology - i.e. GM corn adoption. Importantly, this measure is only based on exogenous soil and weather characteristics and not on observed yields, which are endogenous to the technology adoption[19]. The variation used to identify the effect is therefore the potential increase in yields, which we assume to be correlated (although not perfectly) with the actual yield gain[20]. Although GM corn introduction is not the only

[18]In case of split/merge between municipalities over the course of the study period, I always aggregate barangays to form the largest stable entities. I am grateful to Andres Ignacio from ESSC for providing me his match between the PSGC 2000 and PSGC 2010.

[19]Given that most of the corn cultivation in the Philippines is rain fed, we use the data under this water source regime.

[20]In a cross-country analysis, Alvarez and Berg (2019) show that potential yield is positively correlated with actual yield, especially so in East Asia and Pacific region (R^2=0.46).

explanation for the increasing corn yields over the period, it is the most important technological change and is therefore likely to have largely contributed to it. For the sake of readability, in the rest of the paper, when we talk about the potential gain from GM corn, we are therefore referring to the overall change in profitability, which is largely driven by the new technology.

Summary statistics of the corn potential yields, with different levels of input, are presented in Table 4. They are expressed in tons per hectare, with the last row presenting the difference between high and low levels of inputs. Moving from low to high level of inputs more than triples the potential yield, with some regions gaining as much as four times the average. These values are lower than the average actual yields given that they are computed over the entire country, including the areas not suitable for agriculture. The geographical distribution of the potential gain in corn yield is presented in Figure 3.

Table 4: Summary statistics of corn potential yield

	Mean	Std Dev	Min	Max
Low input level	0.823	0.452	0	2.116
High input level	2.827	1.585	0	9.805
High - Low	2.004	1.268	0	7.997

Source: FAO GAEZ

This estimation strategy can be formalized with the following equation:

$$y_{it} = \delta_i + \delta_t + \beta A_{it} + \epsilon_{it}, \tag{1}$$

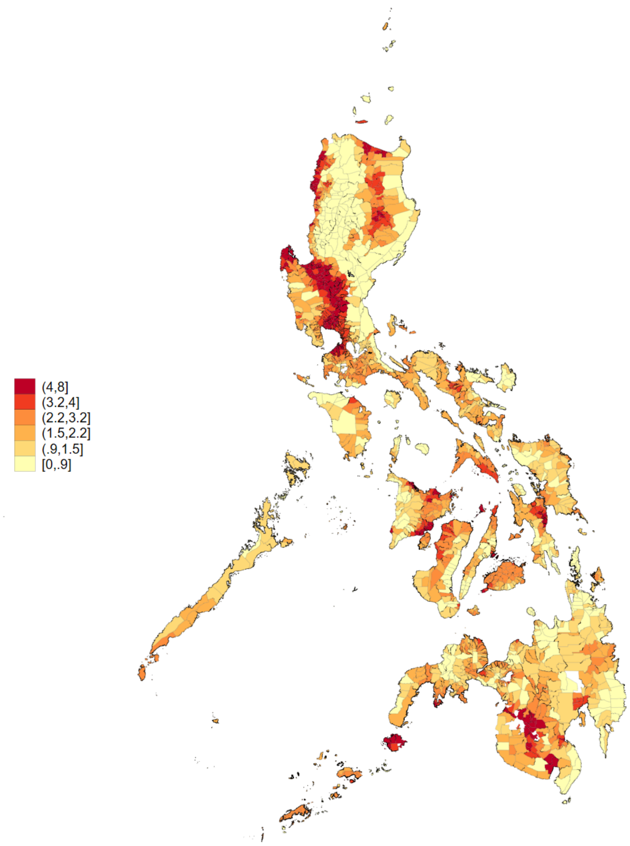
where y_{it} is an outcome variable that varies across municipality i at time t. δ_i and δ_t are respectively municipality and year fixed effects. A_{it} is the measure of potential corn yield, and takes the value under low level of inputs before 2003 and under high level of input after[21]. In the main specifications, the analysis is restricted to the years 2002 and 2012. In that case, the fixed effect equation is equivalent to the first difference model

$$\Delta y_i = \Delta\delta + \beta\Delta A_i + \gamma_1 X_i + \gamma_2 Z_{i,1991} + \Delta\epsilon_i \tag{2}$$

β, our coefficient of interest, reports how the outcome variable changes between two periods following an increase in potential yield due to the introduction of the new agricultural technology. Estimates of β have a causal explanation provided that changes in potential yields are independently distributed from the outcome variable once we control for all time-invariant characteristics and common shocks. If areas that benefited more from the technology were on different trends from those who benefited less, this assumption would be violated and the estimates would be biased. To alleviate this concern, I

[21] The agricultural sector obviously did not change from being completely traditional to being fully mechanized with the introduction of GM corn seeds. The results hold when intermediate levels of inputs are used either in the pre- or in the post-adoption period

Figure 3: Geographical distribution of potential corn yield gain



include time-invariant geographical controls X_i and socio-economic indicators computed from the CAF 1991, $Z_{i,1991}$.

X_i include the log of municipal area and, in some specifications, elevation, ruggedness, longitude and latitude. Controlling for these last four variables is however problematic as they enter the formula used to compute the potential yield A_i. The interpretation of the coefficient β is therefore going to be different when they are included. On the other hand, excluding them may bias the estimates as they are correlated to other determinants of land inequality trends, such as market access or the occurrence of natural disasters. In a robustness check, I show that the results hold when each variable is added individually.

Trends in land inequality and technology adoption are likely to differ depending on baseline land scarcity. In frontier regions where new land can be cleared, we would expect lower agricultural productivity and different land market dynamics compared to places where all the land is already under cultivation. For this reason, $Z_{i,1991}$ includes the share of total municipal area dedicated to agriculture in 1991. Moreover, over the study period, corn prices have experienced a sharp increase, being multiplied by three between 2002 and 2012 (IMF, 2021). This implies that regions where corn production is more widespread are on a different trend. As these regions are likely to be those with a high suitability, I also control for the share of corn in total agricultural area in 1991. Finally, night light intensity in 1992 controls for a combination of initial population density and economic development[22].

5 Results

5.1 First-stage effect

The empirical strategy is based on the assumption GM corn introduction had a stronger impact in areas which had higher potential gains. Unfortunately, the agricultural census does not distinguish between different corn varieties and does not provide output information. While it is therefore impossible to provide strong evidence that adoption and yield gains were higher in more suitable areas, the present section, discusses and presents suggestive evidence of such a first stage effect[23]. Note that a strong positive correlation between GM corn adoption and potential yield is actually not needed to identify the effect. As previously explained, the technology was rapidly and widely adopted by the farmers, leading to a strong increase in yields. Assuming that the adoption rate was the same over the entire country - and therefore uncorrelated with crop suitability - we would still expect more suitable regions to be more impacted by the new technology.

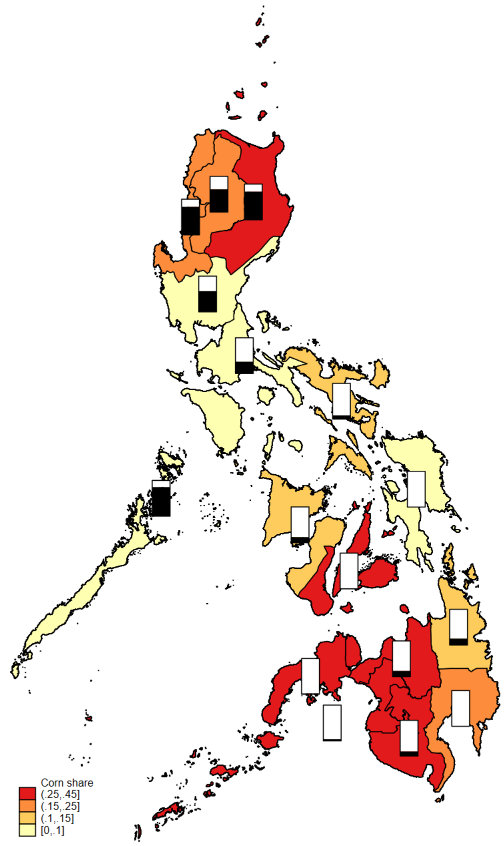
Figure 4 presents the share of agricultural area devoted to corn in each region in the 2012 census, along with the share of GM corn in 2014. To the best of my knowledge, this is the most disaggregated data on GM corn adoption, coming from the Department of Agriculture, which is only available at the regional level for the years 2003-2009 and 2014. Adoption is particularly high in Luzon, which coincides with the high potential yield gain documented in Figure 3. In the Visayas and Mindanao, adoption is almost inexistant. Official agricultural data however understimate the actual adoption of improved corn seeds in these regions as this is precisely where the illegal *sige-sige* seeds can be found. Adoption of those illegal seeds during our study period is likely to be highest in Southern Mindanao, its alleged origin region, which is where potential yield gain is also high.

I now turn to the impact of the new technology on corn cultivation. The results of estimating Equation 2 on the importance of corn cultivation are presented in Table 5. Columns 1 and 3 document a positive correlation between potential gain and the importance of corn cultivation measured as the difference in the log of corn area and the change in the share of agricultural land devoted to this crop. Adding control variables in columns 2 and 4 does not affect the result and even increases the point estimate for

[22]In a recent paper, Gibson et al. (2020) challenge the ability of night lights data to accurately measure economic development in rural areas. They show that this data is particularly unreliable when aggregated over small areas - due to blurring and overglow - and for temporal comparisons - because of satellite change and sensor adjustment to moon light. Given that we aggregate the data at the municipality level and only use one cross-section, these concerns are unlikely to bias our results. Moreover, Gibson et al. (2020) show that night lights are more correlated with economic activity in urban areas, while sparesely populated rural areas remain dark even after electrification. Our municipality-level night lights measure therefore captures the development of the urban center and acts as a proxy for the local market.

[23]Bustos et al. (2016) are able to directly address this question and find that the soy potential yield gain is positively correlated with the change in GM soy area share and negatively correlated with the change in non-GM soy area share (Table 6).

Figure 4: Geographical distribution of corn cultivation and GM corn adoption in 2014



corn area. The magnitude of the coefficients imply that a one-standard deviation increase in potential yield leads to a 0.13-standard deviation increase in corn share, corresponding to an increase in 1.5 percent or 72 hectares for the average municipality. This brings credibility to the estimation strategy as farmers react differently to the technology depending on the soil and weather characteristics of their land.

Table 6 presents the correlation between the potential gain from GM corn and agricultural productivity. Because the CAF do not contain information on output or productivity, I use the the Net Primary Productivity (NPP) as a proxy. This satellite-based indicator measures the difference between the carbon dioxide taken by plants through photosynthesis and the carbon dioxide emitted through respiration. It therefore corresponds to the flow of carbon stocked in plants over a given period and is used as a proxy for vegetation growth, crop yield, forest production etc. The dependent variable is the change in NPP between 2001-03 and 2011-13. Because of to strong seasonal variation in the measure, I take the average value over the three years surrounding the CAF data collection. Column 1 documents a positive relationship between potential yield and productivity when no control variable is included. This positive effect decreases and becomes insignificant when we control for other determinants of NPP, such as the change in tree cover and in crop shares. The interaction between the change in corn share

Table 5: Productivity change and corn cultivation

VARIABLES	(1) Δ Corn area (Log)	(2)	(3) Δ Corn share	(4)
Potential gain from GM corn	0.071***	0.120***	0.012***	0.012***
	(0.027)	(0.029)	(0.003)	(0.003)
Municipality area (Log)		-0.028		-0.017***
		(0.041)		(0.004)
1991 Ag area (Share)		-0.402***		-0.073***
		(0.135)		(0.014)
1991 Corn share		-0.054		-0.060***
		(0.112)		(0.013)
1992 Night lights (Log)		-0.089***		-0.005***
		(0.027)		(0.002)
Observations	1,520	1,434	1,520	1,434
R-squared	0.005	0.020	0.019	0.090

Changes in dependent variables are calculated over the years 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

and the potential yield gain, in columns 3 and 5, yield positive and statistically significant coefficients. This provides suggestive evidence that the new technology did lead to an increase in corn production in more suitable areas.

5.2 Land inequality

We now turn to the effect of agricultural productivity on the landholding distribution. The first two columns use the percentage point change in landholding Gini as dependent variable and show that this measure is positively correlated with the profitability of the technology. When we control for municipal area and differential trends based on agricultural importance and economic development, the coefficient remains relatively stable but loses some significance. Similar results are obtained in the last two columns which use the land share of the top decile as dependent variable. To improve the readability of the tables, the dependent variables are expressed in percentage points, i.e. ranging from 0 to 100 instead of 0 to 1. Results with control variables imply that a one-standard deviation increase in potential yield leads to a 0.6-point increase in the Gini index and a 0.7-percentage point increase in the top 10% share.

The impact of the new technology on the landholding distribution is presented in Figure 5, which replicates the last column of Table 7 using each decile land share as outcome variable. The change in inequality appears to be driven by the increase in the land share of the top decile and a decrease of all the other deciles, although this last effect is not always statistically significant.

Table 6: Productivity change and Net Primary Productivity

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GE corn	0.582**	0.127	0.031	0.418	0.334
	(0.251)	(0.294)	(0.310)	(0.315)	(0.330)
Potential gain * Δ Corn share			4.098**		3.999*
			(2.067)		(2.096)
Δ Tree cover (Share)		0.268**	0.277**	0.256**	0.266**
		(0.108)	(0.108)	(0.107)	(0.107)
Δ Corn (share)		-4.618	-14.144**	-3.784	-13.085**
		(3.663)	(5.929)	(3.790)	(6.049)
Observations	1,520	1,520	1,520	1,506	1,506
R-squared	0.003	0.052	0.055	0.066	0.068
Crop controls	NO	YES	YES	YES	YES
Additional controls	NO	NO	NO	YES	YES

Dependent variable is the difference in NPP average over the 2001-03 and the 2011-13 periods. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Crop controls include the change in crop share for corn, rice, sugarcane, coconut, banana, other temporary and other permanent crops. Additional controls include log of municipality area, log-change in farm area, number of farms, population, night light intensity and the change in rural population share.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.3 Mechanisms

A change in the land distribution can be explained by three potential mechanisms : (i) a reallocation of the previously-farmed land between farmers, (ii) an expansion (or contraction) of the farm area and (iii) an increase (or decrease) in the number of farms. These mechanisms are not mutually exclusive as a new farm can encroach on new land, thereby also increasing agricultural area.

To disentangle the different mechanisms, Table 8 first documents the correlation between agricultural productivity and the change in farm area and in farm number. Column 1 shows a weakly significant, positive correlation between the potential gain from GM corn and agricultural area. The magnitude of the coefficient implies that a one-standard deviation increase in potential productivity leads to a 3.17% increase in cultivated area, corresponding to 153ha for an average municipality. This however does not necessarily imply agricultural land *expansion* in more affected municipalities as this effect is a relative one, comparing places more and less affected by the technology. As the general trend over the period is a contraction in agricultural land, it is possible that the positive effect corresponds to a smaller decrease in farm area. Column 2 shows that the farm number does not react to the change in agricultural productivity and is therefore not driving the relative expansion.

Table 7: Productivity change and landholding inequality

VARIABLES	(1)	(2)	(3)	(4)
	Δ Gini		Δ Share top decile	
Potential gain from GM corn	0.531***	0.459**	0.583***	0.554**
	(0.191)	(0.210)	(0.214)	(0.239)
Municipality area (Log)		1.074***		1.212***
		(0.301)		(0.346)
1991 Ag area (Share)		3.624***		2.737**
		(0.964)		(1.104)
1991 Corn share		0.540		1.436
		(1.044)		(1.191)
1992 Night lights (Log)		0.362**		0.418**
		(0.183)		(0.203)
Observations	1,520	1,434	1,520	1,434
R-squared	0.006	0.025	0.006	0.023

Changes in dependent variables are calculated over the years 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality. Robust standard errors in parentheses.

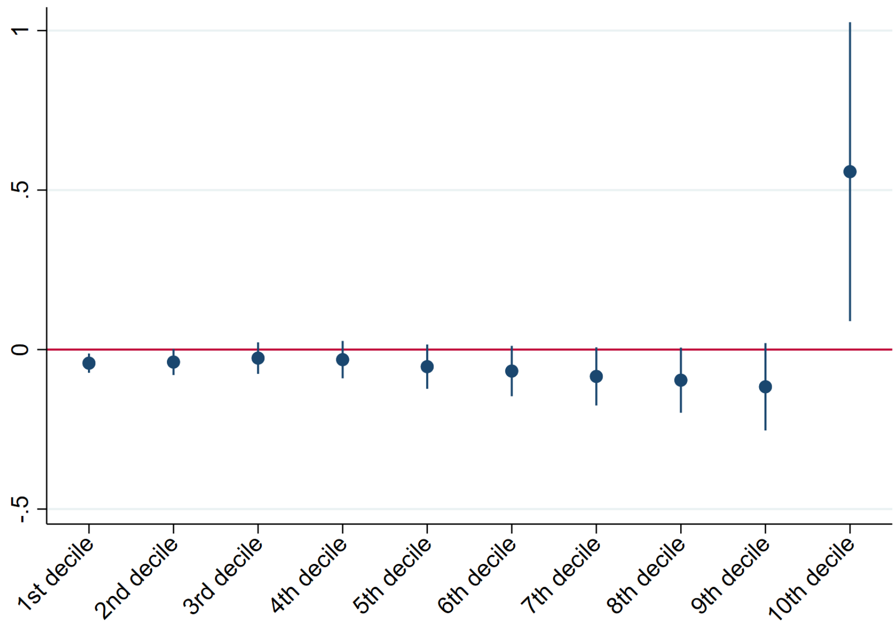
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The rest of the table uses the change in Land Gini as dependent variable, with column 3 replicating the result from Table 7. Columns 4 and 5 respectively control for the change in farm area and that in farm number and column 6 includes both. The coefficient of potential gain from GM corn decreases and becomes insignificant when controling for the change in agricultural area. On the other hand, it does not change when controling for the change in farm number, which was expected given the non significant result in column 2. Adding both controls together further reduce the point estimate, which becomes statistically different from that of column 3 at the 10% level. This indicates that land reallocation between existing farmers does not play an important role and that the increase in land inequality is driven by municipalities that experienced a relative increase in agricultural land and a relative decrease in the number of farms. Using the share of top decile instead of the Gini index as dependent variable leads to very similar results (Table D.1 in the Appendix).

Understanding whether this relative increase in farm area corresponds to an actual farmland expansion or to a smaller contraction is an important question from an environmental perspective. To address this issue, I re-estimate column 4 of Table 8, transforming the change in farm area from a continuous variable to a set of binary variables, each one corresponding to a different quintile of the distribution. Since 77% of municipalities experience a decrease over the decade, only the last quintile is associated with an increase in agricultural area as[24]. As Table D.2 in Appendix shows, the potential gain coefficient decreases strongly when we only control for the first two quintile categories, i.e. when we differentiate municipalities that experienced a strong decrease in agricultural land from the rest. In the opposite,

[24]The distribution of the change in agricultural area is presented in Figure D.1 in Appendix.

Figure 5: Impact of productivity change on land share for each decile



Each point represents the coefficient of potential gain in GM corn from a different regression, using the change in land share devoted to each decile as dependent variables, similar to column 4 of Table 7.

controlling for the last two quintiles - those where there was no change or an increase - does not affect the coefficient of interest. This indicates that the positive correlation between agricultural productivity and land inequality is not driven by an actual expansion of agricultural land, but by a smaller contraction.

5.4 Heterogeneous effects

5.4.1 Modern input and credit penetration

A common story in anti-GMO advocacy is that of predatory lending resulting in farmers taking on too much debt and eventually defaulting. Their lands are then confiscated by the moneylender or they are forced to sell them (Masipag, 2013). As a result, moneylenders or other better-off households are able to increase their landholding, resulting in an increase in land inequality[25]. The CAF data does not provide enough information to precisely test this story but can still give us some suggestive evidence. Indeed, the CAF 1991 asked farming households whether they contracted a credit (formal or informal) over the preceding year. Aggregated at the municipality level, this question gives us a measure of credit penetration 10 years before GM corn was introduced[26]. If such claims were true, we would

[25]This claim is not contradicted by Figure 5 which shows little effect of GM corn at the bottom of the distribution. Indeed, if farmers sell their entire farm, they are removed from the land distribution.

[26]Note that the effect of financial development is a priori not clear. When it is inexistant, only a few wealthy farmers will have the opportunity to adopt the technology and reap its benefits, which should worsen inequality. A high level of credit availability therefore implies that more farmers have access to the technology and its higher yields. In this case, we would expect to see a low level of inequality in municipalities with better access to financial services.

Table 8: Productivity change and landholding inequality - Mechanisms

VARIABLES	(1) Δ Farm area (Log)	(2) Δ Farm nb (Log)	(3) Δ Gini	(4)	(5)	(6)
Potential gain from GM corn	0.026*	-0.011	0.459**	0.317	0.467**	0.101
	(0.013)	(0.013)	(0.210)	(0.205)	(0.210)	(0.192)
Municipality area (Log)	0.076***	0.025	1.074***	0.660**	1.058***	0.462*
	(0.019)	(0.018)	(0.301)	(0.302)	(0.303)	(0.280)
1991 Ag area (Share)	0.133**	0.105*	3.624***	2.891***	3.554***	2.995***
	(0.062)	(0.061)	(0.964)	(0.912)	(0.970)	(0.866)
1991 Corn share	-0.133**	-0.049	0.540	1.270	0.574	1.575*
	(0.052)	(0.047)	(1.044)	(0.982)	(1.048)	(0.899)
1992 Night lights (Log)	-0.067***	-0.051***	0.362**	0.728***	0.396**	0.687***
	(0.012)	(0.012)	(0.183)	(0.180)	(0.187)	(0.176)
Δ Farm area (Log)				5.491***		10.553***
				(0.690)		(0.889)
Δ Nb farms (Log)					0.671	-7.439***
					(0.586)	(0.879)
Observations	1,434	1,434	1,434	1,434	1,434	1,434
R-squared	0.047	0.029	0.025	0.132	0.026	0.215

Changes in dependent variables are calculated over the years 2002 and 2012. Columns 3-6 use the change in landholding Gini index as dependent variable. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

expect to see a stronger effect in municipalities where credit availability is higher. The second column of Table 9 repeats the analysis of the Land Gini, controlling for the degree of credit penetration in 1991 and interacting it with our potential gain measure. None of the additional coefficients are significant, implying that credit may not be an important mechanism.

However, credit penetration is potentially correlated with other agricultural development measures, which may also play a role in our story. The CAF 1991 also asked farmers whether they were cultivating high-yield varieties (HYV) over the past year. Aggregating these responses at the municipality level gives us an indicator of the modernity of agricultural practices ten years before treatment. As Column 3 shows, the effect of potential gain on the Land Gini is highest in municipalities with low HYV use in 1991 and is equal to zero in areas where improved seeds were already widely adopted.

This result first suggests that our main result is driven by municipalities that were lagging behind in the modernization of their agriculture, and therefore where the potential for yield improvement was the largest. Second, since credit and HYV are positively correlated, the results presented in Column 2 might be biased downwards (and those of Column 3 upwards). Indeed, when we allow for different trends depending on both credit and HYV penetration, we respectively find a positive and negative significant coefficient for the interaction terms (Column 4). Moreover, this mechanism remains significant when controlling for the change in farm area (Column 5). The positive effect of agricultural productivity on land inequality is therefore higher in municipalities with better access to financial services. However, this only brings weak supportive evidence to the "default and confiscation" narrative as credit availability is likely to increase adoption and therefore act as proxy for treatment intensity. I am therefore unable to rule out alternative mechanisms linking credit, productivity and

Table 9: Landholding Gini and productivity change - Historical cultivation practices

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GM corn	0.459**	0.340	1.028**	0.796*	0.846*
	(0.210)	(0.410)	(0.441)	(0.459)	(0.434)
Credit 1991		-0.249		-3.030*	-3.048*
		(1.473)		(1.755)	(1.733)
Pot. yield * Credit 1991		0.225		1.956***	1.616**
		(0.623)		(0.729)	(0.727)
HYV 1991			2.328	4.318**	2.800
			(1.530)	(1.839)	(1.814)
Pot. yield * HYV 1991			-1.165*	-2.524***	-2.271***
			(0.670)	(0.809)	(0.781)
Municipality area (Log)	1.079***	1.071***	1.053***	1.021***	0.673**
	(0.302)	(0.306)	(0.302)	(0.304)	(0.304)
1991 Ag area (Share)	3.673***	3.655***	3.580***	3.242***	2.428***
	(0.965)	(0.966)	(0.972)	(0.973)	(0.933)
1991 Night lights (Log)	0.357**	0.360**	0.353*	0.361**	0.702***
	(0.180)	(0.181)	(0.182)	(0.182)	(0.179)
1991 Corn share	0.567	0.632	0.529	0.654	0.945
	(1.044)	(1.066)	(1.057)	(1.058)	(0.992)
Δ Farm area (Log)					5.562***
					(0.706)
Observations	1,435	1,435	1,435	1,435	1,435
R-squared	0.025	0.026	0.028	0.032	0.140

Dependent variable is the change in landholding Gini index, calculated over the years 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

inequality.

5.4.2 Geographical heterogeneity

I now look at heterogeneous effects based on the location of municipalities in order to get a better understanding of the geographical distribution of our main effect. The first three columns of Table 10 allow for differential effects between coastal and interior municipalities. This is motivated by the fact that coastal municipalities are likely to be different from the rest on many levels (exposure to climate events, transportation, communication etc.). The correlation between agricultural productivity and land inequality is only significant for coastal municipalities, and disappears when controling for the change in farm area and in farm number. However, the coefficient is not statistically different from the coefficient for Potential gain * Interior municipalities.

Table 10: Landholding Gini and productivity change - Geographical heterogeneous effects

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Potential gain * Coastal municipality	0.625**	0.605**	0.329			
	(0.269)	(0.283)	(0.248)			
Potential gain * Interior municipality	0.401	0.173	-0.255			
	(0.273)	(0.277)	(0.268)			
Potential gain * Visayas				0.799**	0.609	0.327
				(0.388)	(0.413)	(0.350)
Potential gain * Mindanao				1.169**	1.097**	1.049**
				(0.500)	(0.510)	(0.420)
Potential gain * Luzon				0.401	0.252	-0.131
				(0.251)	(0.261)	(0.247)
Municipality area (Log)		1.037***	0.453		0.923***	0.310
		(0.301)	(0.281)		(0.302)	(0.283)
1991 Ag area (Share)		3.976***	3.338***		2.795***	1.625*
		(0.956)	(0.864)		(0.977)	(0.887)
1991 Corn share		0.148	1.276		-0.240	0.491
		(1.025)	(0.894)		(1.112)	(0.935)
1992 Night lights (Log)		0.364**	0.684***		0.455**	0.833***
		(0.182)	(0.176)		(0.183)	(0.177)
Δ Farm area (Log)			10.476***			10.678***
			(0.889)			(0.897)
Δ Nb farms (Log)			-7.460***			-7.408***
			(0.876)			(0.876)
Coastal municipality	-1.866**	-2.460***	-1.935**			
	(0.946)	(0.934)	(0.852)			
Visayas				-0.619	-0.993	-0.072
				(1.046)	(1.090)	(0.987)
Mindanao				0.865	0.120	0.018
				(1.218)	(1.223)	(1.099)
Observations	1,520	1,434	1,434	1,520	1,434	1,434
R-squared	0.012	0.034	0.218	0.020	0.033	0.225

Dependent variable is the change in landholding Gini index, calculated over the years 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The last three columns presents heterogeneous effect by island group: Luzon (North), the Visayas (center) and Mindanao (South). Without additional controls, the positive effect of agricultural productivity on land inequality is significant for the Visayas and Mindanao (although none is statistically different from the Luzon coefficient). Adding control variables decrease the point estimate for the Visayas but not for Mindanao which remains positive and significant even after controlling for the change in farm area[27]. The increase in inequality due to changes in agricultural productivity is therefore driven by the island of Mindanao and by coastal municipalities.

Figure D.2 presents the results obtained when column 5 of Table 10 is replicated, allowing a differential effect for each region. These regional heterogeneous effects are then mapped in Figure D.3. The results

[27] The coefficient for Mindanao also becomes statistically different from the Luzon coefficient, but not from the Visayas coefficient.

confirm the previous analysis as the four regions with the largest point estimates are located on the island of Mindanao, the effect being strongly different from zero in three of them.

5.5 Land ownership inequality

The analysis so far has focused on landholding inequality, i.e. computing the land distribution using operated farm as the basic unit. However, land *ownership* inequality is also an important measure as it is more closely linked to wealth and poverty. Due to data constraints, it is impossible to repeat the analysis using the same inequality measures for land ownership. Instead, we can look at the share of land that is not owned by the household cultivating it. An increase in that measure indicates an increase in land ownership inequality given that land ownership tends to be less equally distributed than landholding. Similarly, an increase in the share of tenanted farms also indicates more ownership inequality. Table 11 presents the results obtained by estimating Equation 2 using the two aforementioned land ownership measures as dependent variables. The share of tenanted land decreases in municipalities that benefited more from the technology, although this effect loses some significance once we add the control variables (p-value = 0.14). The share of tenanted farms shows similar results, with a positive correlation with the potential gain that becomes insignificant once the control variables are added (p-value = 0.19). Overall this suggests that the increase in landholding inequality is reflected in the land ownership distribution as a smaller proportion of farms own a larger (or similar) share of the land. This may be driven by the land expansion in the last decile of the landholding distribution.

Table 11: Productivity change and land ownership inequality

	(1)	(2)	(3)	(4)
VARIABLES	Δ Tenanted land		Δ Tenanted farms	
Potential gain from GM corn	-0.613**	-0.465	0.606*	0.464
	(0.282)	(0.315)	(0.314)	(0.353)
Municipality area (Log)		-1.383***		-2.408***
		(0.448)		(0.418)
1991 Ag area (Share)		-5.242***		-8.212***
		(1.577)		(1.533)
1991 Corn share		0.567		-3.251**
		(1.483)		(1.426)
1992 Night lights (Log)		-0.284		-0.047
		(0.291)		(0.286)
Observations	1,520	1,434	1,520	1,434
R-squared	0.003	0.016	0.003	0.053

Changes in dependent variables are calculated over the years 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6 Robustness tests

6.1 Crops, population and economic development

The positive effect of agricultural productivity on land inequality might be the result of a move towards more land intensive crops in municipalities that benefited more from the new technology. Corn, however, does not fit this description as it is mostly cultivated by smallholder farmers. As column 2 of Table E.1 in the Appendix shows, land inequality decreases when the corn share increases and adding this control increases (not significantly) the potential gain coefficient. Adding the change in land share for other common crops such as rice, sugarcane, coconut and banana does not have a significant impact (column 3).

Another potential explanation might be that people migrated from low to high productivity municipalities. Such a mechanisms is however unable to explain our results as controlling for the change in population in column 4 does not affect our coefficient of interest. Similarly, the effect of agricultural productivity on land inequality is not driven by differential trends in rural-urban migration as controlling for the share of rural population leads to similar results (column 5). Finally, column 6 controls for the change in night light intensity between 2002 and 2012 and shows that the potential gain coefficient remains unchanged. Adding all the additional controls in a single regression leads to similar results. Changes in crop mix, internal migration patterns or economic development are therefore not driving the relationship between productivity and inequality.

6.2 Topo-geographical characteristics

The empirical strategy used in this paper relies on a measure of potential yield gain, which is computed using soil and weather characteristics. However, these characteristics may affect the trend in land inequality through other channels than land productivity. For example, elevation and ruggedness determine the availability of transport infrastructure and therefore input availability and market access. Similarly, extreme weather patterns affect the accumulation of physical capital, with consequences for the trend in economic development. On the one hand, omitting these variables from the regression, as has been the case so far, might bias our estimates. On the other hand, if we control for them, the potential gain variable loses part of its substance and it is not clear how to interpret the coefficients.

To address this issue, I re-estimate the main regression for the landholding Gini, adding topo-geographical control variables and present the results in Table E.2 in the Appendix. In order to keep some informational value in the potential gain variable, the controls are added individually in each regression. Columns 2 and 3 control for average elevation and ruggedness index. In both cases, the point estimate becomes larger and more significant, indicating that, if anything, the omitted variable bias was pushing our coefficient downwards. Column 4 controls for longitude and latitude, which is strongly correlated with weather patterns, especially extreme weather since tropical cyclones hit the northern half of the country on a yearly basis while missing almost systematically the southern part. The inclusion of these variables does not impact our result. Finally, the last column assumes that trends in land inequality differ at the provincial level and therefore allows for province fixed effects. While the value of the coefficient does not change much, its significance decreases (p-value = 0.156).

6.3 Pre-treatment trends

One of the key identifying assumptions in our estimation strategy is that trends in land inequality are uncorrelated with the potential yield gain once we control for municipal area and pre-determined variables. This would be violated if previous productivity growth had already put more profitable areas on different trends. One way to test this hypothesis is to run the same analysis, comparing data from 1991 and 2002, i.e. before the introduction of GM corn. Results of this placebo test are presented in Table E.3. Note that, contrary to what we have done so far, municipality-level measures of land inequality are not computed from the same set of barangays given the sampling method of the CAF 1991 and 2002. It is therefore impossible to rule out the fact that the results presented in this table are partly due to sampling differences[28].

When no controls are included, we find an insignificant, negative, correlation between potential yield gain and the change in Gini index or in the top decile land share. This effect slightly increases but remains insignificant when we control for municipal area, agricultural land share, corn share and night light intensity. Similar results are obtained with the land share of the top decile, giving little support for potential different trends before GM seeds introduction.

Table E.4 pools the three waves of CAF data into a single regression, therefore combining the results of Table 8 and Table E.3. The results are in line with those previously reported, with a non significant effect of potential gain between 1991 and 2002 and a positive and significant effect between 2002 and 2012. Pooling all the data also allows to control for different trends at the municipality level through municipality fixed effects. When adding those (columns 3 and 6), the effect of potential gain in the second period remains positive and statistically significant.

6.4 Spatial correlation

Given that soil and weather characteristics are not distributed randomly over the country, potential corn yield is likely to exhibit some level of spatial auto-correlation. Not taking this into account leads to an underestimation of standard errors, thereby increasing the probability of excluding the null hypothesis when we should not. For this reason, Table E.5 reports the p-value obtained when re-estimating our main results with alternative clustering techniques. The first row shows the p-values obtained from the robust standard errors that we have used so far. The second and third rows presents p-values after the correction suggested by Conley (1999) using a 25-km and a 50-km radius and the last row when standard errors are clustered at the provincial level. When control variables are not included, the coefficients remain below the 5% threshold with the 25-km radius and below the 10%

[28] The use of sampling weights should however largely alleviate this issue.

with the 50-km radius. When controls are included, p-values are larger but always remain below 15%. Provincial-level clustering yields standard errors somewhere between the two radius values.

6.5 Barangay-level analysis

Due to the geographic characteristics of the country, the level of within-municipality heterogeneity in the Philippines tends to be high. For example, the median municipality area is equal to 119 sq km and the median elevation range(difference between highest and lowest altitude) is 543m, reflecting the hilliness of the country. Similarly, the within-municipality standard deviation in potential yield is equal to 0.65 on average, which correspond to half of the standard deviation computed between municipalities. Given this heterogeneity, we cannot be sure that the increase in land inequality is actually observed in areas that became more productive or is the result of spill-over effects coming from nearby areas.

To address this issue, I repeat the analysis using barangay-level data and present the results in Table E.6. Before interpreting the results, it is important to remind the differences between barangay- and municipality-level data. First, the plot physical location is only available at the municipality-level. Barangay land inequality measures are therefore computed on the total land cultivated by people living in the barangay, not on the land located within its boundaries. While both sets are the same in most cases, large farms straddling administrative boundaries and absentee landlords will create a wedge between them. It is therefore possible to have a value of agricultural area larger than the total barangay area, which was not the case in the municipality data. Second, due to the sampling method used in the successive rounds of the CAF, the number of observations will vary depending on the variables included in the analysis. More specifically, when controlling for 1991 variables, the observation number will strongly decline as we only use the balanced sample over the three waves[29]. Third, while municipalities with less than 50 ha of agricultural land were excluded from the analysis, this threshold is decreased to 10 ha for barangays. Once again, this avoids taking into account areas where farming is a marginal activity. Finally, while most municipalities comprise both urban and rural areas, barangays usually fall in only one of those categories. Given that agricultural land inequality is not a relevant issue in urban areas, it makes sense to restrict the sample to rural barangays only .

Results from Table E.6 are remarkably similar to those from Table 8, especially when we restrict the analysis to rural barangays (Columns 3 and 6). In those barangays, a one-standard deviation increase in potential yield leads to a 1.1-point increase in Gini coefficient and a 0.6-percentage point increase in the top decile land share. The results obtained at the municipality level are therefore unlikely to be driven by spill-over effects.

[29]See Appendix A.5. for the details regarding the sampling structure and the weights recomputation.

6.6 Alternative measures of inequality and productivity

The measure of potential gain from GM corn that we have used so far was defined as the difference between the potential corn yield with high and low levels of input. The high level corresponds to optimal modern agricultural practices while the low level corresponds to traditional practices with no external inputs. The agricultural sector in the Philippines, however, did not change from being completely traditional to being fully mechanized over the decade 2002-2012 and the introduction of GM seeds can certainly not account for such a drastic change.

As an additional robustness test, I use alternative measures of potential gain from GM corn, re-computing it using the potential yield with intermediate levels of inputs either in the pre- or in the post-adoption period. The first four columns of Table E.7 presents the results when it is defined as the difference between intermediate and low levels of inputs; the last four columns when it is defined as the difference between high and intermediate levels of inputs. Results are in line with those presented in the rest of the paper. When using the difference in yield between intermediate and low levels of inputs, however, the effect is much less precisely estimated and becomes insignificant. This is the result of the lower variation in potential gain with this definition: the standard deviation is 0.35 compared to 1.27 when we take the difference between high and low levels of inputs. This decreases the statistical power of the analysis, leading to a non rejection of the null hypothesis although the point estimates are twice larger than in the baseline regressions.

7 Land inequality and socio-economic outcomes

Results presented in this paper document an increase in landholding inequality following the introduction of GM corn in the Philippines. Since land inequality has been shown to have adverse effect on welfare and economic development, the question of the net effect of the technology needs to be addressed. In other words, is the increased inequality a small price to pay given the gain in agricultural productivity? To investigate this question, the present section focuses on three types of indicators: (i) Municipality-level poverty rates, (ii) income and expenditure data from a representative household survey and (iii) terrorist activity. The following results are only correlational and potentially subject to reverse causality as they are not identified on any exogenous variation in the land distribution.

7.1 Poverty incidence

The first socio-economic outcome investigated is poverty incidence, measured at the municipality level by Philippines Statistics Authority (2016) using the methodology developed by Elbers et al. (2003). This methodology combines census data, providing comprehensive coverage but limited information, with survey data, which provides extensive information for a smaller sample. This allows the computation of small area statistics, including poverty rates. For the Philippines, such measures are available for the years 2000, 2003, 2006, 2009 and 2012. However, a change in methodology in 2006 makes the 2000 and 2003 estimations impossible to compare with the later ones.

Table 12 presents the correlation between the 2012 poverty level and land inequality. Because the dependent variable is an estimation, the standard errors of all regressions are bootstrapped. In order to improve readability, all variables are expressed as percentage points - i.e. between 0 and 100 instead of 0 and 1. The first column shows that municipalities with a more unequal land distribution tend to have a lower poverty level as both contemporaneous and 10-year lagged inequality are negatively correlated with poverty. The coefficients size imply that poverty increases by 2.8 and 1.6 percentage points when the lagged and contemporaneous land inequality respectively increase by one standard deviation. Using our measure of potential gain from GM corn, Column 2 shows that municipalities with a higher potential gain also have a lower poverty rate. A one-standard deviation increase in potential gain is associated with a 5.4 percentage point decrease in poverty.

Table 12: Municipality-level poverty rate

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2012 Land Gini	-0.152**		-0.120**	-0.097***	-0.198***		-0.039	-0.001
	(0.061)		(0.053)	(0.034)	(0.062)		(0.051)	(0.041)
2002 Land Gini	-0.311***		-0.099	-0.086**	-0.159***		-0.035	-0.045
	(0.057)		(0.062)	(0.042)	(0.046)		(0.042)	(0.042)
Potential gain from GM corn		-4.224***	-3.175***	-1.582***		-2.830***	-1.152***	-0.378
		(0.264)	(0.298)	(0.236)		(0.321)	(0.420)	(0.330)
2006 Poverty rate				0.636***				0.598***
				(0.019)				(0.029)
Observations	1,520	1,574	1,518	1,518	1,520	1,574	1,518	1,518
R-squared	0.052	0.102	0.350	0.588	0.056	0.091	0.313	0.584
Province FE	NO	NO	NO	NO	YES	YES	YES	YES
Controls	NO	NO	YES	YES	NO	NO	YES	YES

Dependent variable is an estimation of municipality poverty rate in 2012, using the methodology developed by Elbers et al. (2003). Control variables included in columns 3, 4, 7 and 8 are population (log), share of rural population, share of farming households and share of agricultural land. These variables are computed using the 2010 Census of Population and the 2012 Census of Agriculture and Fisheries. Standard errors are bootstrapped.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Column 3 combines land inequality and corn productivity in the same regression and adds demographic and economic controls (log of population, share of rural population, share of farming households and share of agricultural land). All coefficients slightly decrease and the 10-year lagged land inequality becomes insignificant. Adding the 2006 poverty rate in column 4 allows us to investigate the correlation between land inequality and the *change* in poverty. The results are remarkably similar to those previously reported: the change in poverty rate is negatively correlated both with the 10-year lagged and with contemporary land inequality. This implies that places that became more unequal over the decade experienced a stronger decrease (or smaller increase) in poverty. However, when provice fixed effects are added in Columns 5-8, this correlation strongly decreases and becomes insignificant, indicating that it was largely driven by unobserved heterogeneity.

7.2 Household survey data

The Family Income and Expenditure Survey (FIES), carried out by the Philippine Statistical Authority every three years, collects repeated cross-sectional data on income and expenditure from a representative sample of the Philippine population. The sample size varies from 20,000 in the 1990s to around 40,000 after 2000. The analysis below uses the closest data from the agricultural census, namely the FIES 2003 and 2012. Investigated outcome variables include the logarithm of per capita income and expenditure and dummy variables equal to one if the household head is employed and is a farmer. I also use the national poverty lines at the time of survey to categorize households as poor and non-poor[30]. Finally, I create two additional variables, indicating whether the household is in the bottom quintile or in the top decile of the national per capita income distribution. In contrast with the rest of the paper, the analysis is run at the level of the household and not the municipality. The estimated equation is given by

$$y_{ijt} = \delta_j + \delta_t + \beta_1 Gini_{jt-1} + \beta_2 Gini_{jt} + \gamma_1 X_{ijt} + \gamma_2 Zjt + \epsilon_{ijt}, \tag{3}$$

where y_{ijt} is the outcome variable of household i, living in municipality j at time t. δ_j and δ_t are respectively municipality and year fixed effects. X_{ijt} and Z_{jt} control for household characteristics (family size, head's gender, age and education) and for time-varying municipality characteristics (log of farm number, log of farm area and potential corn yield[31]) respectively. β_1 gives the conditional correlation between the 10-year lag in landholding inequality and the dependent variable. This variable is included because we expect land inequality to have a lagged effect on income and expenditure. As the past land inequality is included in the regressions, β_2 gives the conditional correlation between the change in land inequality and the dependent variables[32]. The error term ϵ_{ijt} is clustered at the municipality level. The equation is estimated using OLS for all the outcome variables.

The first panel of Table 13 shows the results when only year fixed effects and household characteristics are included. Households living in municipalities where land was more unequally distributed in the past are more likely to be employed and less likely to have agriculture as their main occupation. Contemporaneous land inequality is positively correlated with income, expenditure and employment and negatively correlated with the probability of being a farmer and of being poor. Coefficient sizes imply that an increase in past inequality by one standard deviation is associated with an incresed probability of being employed of 2.3 percentage points. An increase in contemporaneous inequality by one standard deviation is associated with an increase in income of 4.4% and a decrease in the probability of being poor by 2 percentage points.

Panel B reports the results when we include municipality fixed effects and time-varying control variables. The inclusion of these variables strongly decrease the coefficients of present and past land inequality, which all become insignificant. Interestingly, households living in municipalities that experienced a stronger increase in potential corn yield have lower income and expenditure and are more likely to be farmers and poor. An increase of potential gain by one standard deviations is associated with a decrease in income by 2.6% and an increase in the probability of being poor by 1.5 percentage

[30]Households are categorized as poor if their per capita income is lower than PHP 12,267 in 2003 and lower than 18,395 in 2012.

[31]This variable takes the value of the potential yield with low inputs in 2002 and with high inputs in 2012.

[32]Contrary to other tables in this paper, the Land Gini variable is not expressed as percentage points and therefore takes values between 0 and 1.

points.

Table 13: Income, expenditure and employment

VARIABLES	(1) Income	(2) Expenditure	(3) Head employed	(4) Head farmer	(5) Poor	(6) Bottom quintile	(7) Top decile
PANEL A - WITHOUT MUNICIPALITY CONTROLS							
Past Land Gini	0.054	0.117	0.251***	-0.207***	-0.001	-0.014	0.002
	(0.124)	(0.122)	(0.052)	(0.076)	(0.058)	(0.053)	(0.027)
Land Gini	0.467***	0.524***	0.374***	-0.286***	-0.217***	-0.195***	0.083***
	(0.114)	(0.108)	(0.052)	(0.071)	(0.054)	(0.051)	(0.024)
Observations	66,939	66,939	66,939	66,939	66,939	66,939	66,939
R-squared	0.480	0.511	0.134	0.154	0.220	0.208	0.182
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality controls & FE	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PANEL B - WITH MUNICIPALITY CONTROLS							
Past Land Gini	0.003	0.021	0.047	0.134	0.019	-0.001	-0.021
	(0.107)	(0.093)	(0.082)	(0.104)	(0.063)	(0.059)	(0.031)
Land Gini	-0.084	-0.017	-0.002	0.145	0.020	0.003	-0.035
	(0.116)	(0.098)	(0.073)	(0.095)	(0.074)	(0.066)	(0.029)
Potential corn yield	-0.020***	-0.012**	-0.002	0.019***	0.011***	0.005*	-0.004**
	(0.006)	(0.005)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)
Observations	66,939	66,939	66,939	66,939	66,939	66,939	66,939
R-squared	0.593	0.640	0.190	0.238	0.347	0.337	0.214
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality controls & FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Data from the FIES 2003 and FIES 2012. For households observed in 2003 and 2012, past land Gini corresponds to the landholding Gini index computed at the municipality level in 1991 and 2002 respectively. Land Gini corresponds to the landholding Gini index computed at the municipality level in 2002 and 2012 respectively.
Columns 1 and 2 use per capita log income or expenditure. Columns 3-7 use dummy variables as dependent variables.
Household control variables include household head's gender, age, education level and household size. Municipality control variables include the log of farm number and of agricultural area.
Robust standard errors clustered at the municipality level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

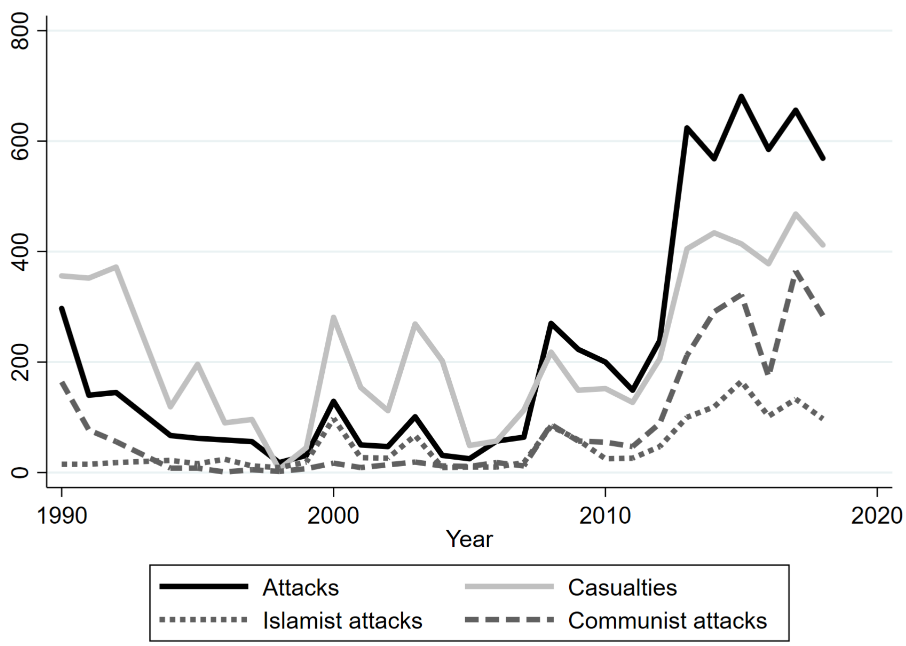
Similar results are obtained when the sample is restricted to households for whom farming is the main occupation (see Table F.1 in Appendix). Without municipality controls, past land inequality is positively correlated with the probability of being employed. Contemporaneous land inequality is positively correlated with income, employment and negatively correlated with poverty. When municipality controls are added, all correlations become insignificant. Once again, potential gain in corn productivity is negatively correlated with income and positively correlated with poverty. This might reflect the fact that corn farming - even with improved inputs - is mostly carried out by poor smallholder farmers. Although those results are only correlational, they do not provide any evidence suggesting a strong negative impact of land inequality on socio-economic indicators.

7.3 Terrorist activity

Since the beginning of the 21st century, the Philippines have been faced with an increase in terrorist activities, perpetrated by left-wing guerilla and islamist insurgency groups. While part of this increase can be attributed to geopolitical events, such as the rise of islamist terrorism, some scholars have attributed this to the unequal distribution of assets between ethnic groups, especially in the South of the country (McDoom et al., 2019). The present section investigates potential links between land inequality and terrorist attacks reported in the Global Terrorism Database (GTD). This database was created by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) from the University of Maryland and compiles newspaper reports of terrorist activities across the world.

Figure 6 reports the yearly number of attacks and casualties, between 1990 and 2018. Over the entire period, 24.5% of attacks are attributed to islamist terrorism while 46.4% are attributed to communists[33]. Following a decrease in the 1990s, the number of attacks, especially involving communist groups, and the number of casualties sharply rise between 2005 and 2015. The geographical distribution of the attacks is reported in Figure G.1 in the Appendix. Most of the events occur on the island of Mindanao. Islamist attacks are concentrated in the West and the South of the island while communist attacks are more common in the East of Mindanao and also happen in other parts of the country.

Figure 6: Temporal variation in terrorist activity at the national level



In order to test the correlation between land inequality and terrorist activity, I use the data provided by the GTD aggregated at the municipality-year level. While previous regressions in this paper were always comparing two data points ten years apart per municipality, the model estimated here is different:

$$y_{it} = \beta Gini_{it} + \gamma X_{it} + \delta_i + \delta_t + \epsilon_{it}, \tag{4}$$

Where y_{it} is the number of terrorist attacks or of casualties in municipality i in year t, comprised between 1991 and 2012. Control variables in X_{it} include the log of agricultural area and of night light intensity, which control for changes in the size and sectoral composition of the local economy.

[33]Note that the perpetrator is categorized as Unknown in 34.9% of the cases

Yearly values for the land Gini and control variables are computed from the CAF data using linear interpolation. As a result, the number of observation strongly increases, from 3 to 22 per municipality. δ_i and δ_t represent municipality and year fixed effects and account for any unobservable time-invariant and aggregate shocks, such as geographical characteristics, geopolitical situation and methodological changes in terrorism data collection. As terrorist attacks are relatively rare events, including municipality fixed effects strongly decrease the number of observations. This also leads to a sample selection issue as municipalities that have not been affected by an attack are excluded from the estimation. As a result, municipality fixed effects are replaced in some regression by province time trends. Finally, the error term ϵ_{it} is clustered at the provincial level to take into account the spatial correlation in terrorist activity. Due to the high number of zero values in the dependent variables (96% of municipality-year cells do not experience an attack), the equation is estimated using pseudo-Poisson maximum likelihood, which is the most appropriate estimator for panel count data with excess zeros.

Table 14: Terrorist attacks

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All		Islamist		Communist	
Land Gini	3.901***	2.560**	4.582**	1.984	1.258	1.985
	(1.203)	(1.147)	(1.792)	(2.773)	(0.925)	(1.218)
Observations	29,206	10,102	8,820	2,131	26,002	5,612
Year FE	YES	YES	YES	YES	YES	YES
Province time trend	YES	NO	YES	NO	YES	NO
Municipality FE	NO	YES	NO	YES	NO	YES
Land Gini	0.821	2.566***	1.095	1.801	-0.019	2.571*
	(1.394)	(0.883)	(2.182)	(2.287)	(0.882)	(1.418)
Log Agricultural land	0.532***	-0.226***	0.564**	-0.628***	0.630***	-0.174
	(0.130)	(0.083)	(0.283)	(0.231)	(0.103)	(0.169)
Log Night light	0.619***	-0.385***	0.644***	-0.388	0.220***	-0.399**
	(0.068)	(0.126)	(0.164)	(0.313)	(0.064)	(0.159)
Observations	29,197	10,102	8,818	2,131	25,994	5,612
Year FE	YES	YES	YES	YES	YES	YES
Province time trend	YES	NO	YES	NO	YES	NO
Municipality FE	NO	YES	NO	YES	NO	YES

Poisson pseudo-maximum likelihood with fixed effects regressions. Unit of observation is the municipality, each municipality is observed every year between 1991 and 2012.
Robust standard errors clustered at the provincial level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The first two columns of Table 14 show that land inequality is positively correlated with terrorist attacks when either province time trends or municipality fixed effects are included. When we add economic control variables, the point estimate only remains significant in the municipality fixed effect regression (Column 2). A similar effect can be found when distinguishing between islamist and communist attacks. However, when controls are included, the correlation only remains significant for communist attacks and with municipality fixed effects. This indicates that land inequality is associated with a higher intensity of attacks in areas where terrorist groups were already operating rather than in regions that were previously spared. Table G.1 in the Appendix presents similar results, using the number of casualties as dependent variable. Although these results may be subject to reverse causality and omitted variable bias, this provides some suggestive evidence that political instability in the Philippines feeds of the unequal distribution of land.

8 Discussion

Municipalities that benefited more from improved agricultural productivity experienced an increase in landholding inequality over the decade 2002-2012. According to our main results from Table 7, gains in productivity induce, on average, an increase in land Gini of 0.9 percentage points. Over the period, the municipality-level Gini index increased by an average of 0.45 percentage points, which implies that, without productivity gain, landholding inequality would have actually decreased by 0.5 percentage points on average. Further analysis documents that this effect strongly decreases when we control for the change in agricultural land. More precisely, municipalities that experienced larger yield gains are less likely to decrease their land devoted to agriculture, which is negatively correlated with land inequality. The main effect is therefore not mediated by an *increase* in agricultural land in more affected municipalities but by a *smaller decrease*, thereby alleviating environmental concern surrounding land encroachment on the remaining forests of the Philippines.

Heterogeneity analysis reveals that the positive relationship between productivity and inequality is not equally present across time and space. More specifically, it does not hold for the 1991-2002 period, the decade preceding the introduction of GM seeds, which nonetheless experienced some gains in corn yields. The nature of the technological change therefore appears to matter. In addition, spatial heterogeneity analysis reveals that the effect is only statistically significant at the 10% level in 7 out of the 16 regions of the Philippines. Unfortunately, the agricultural census lacks detailed information on input and output, preventing us from linking the productivity increase to changes in the agricultural production function which could explain the movements observed in the landholding distribution.

A priori, given that seeds and other inputs can easily be divided, GM corn technology appears to be scale neutral. There are, however, two reasons to believe this may not be entirely true. First, large farmers can buy their inputs in bulk and pay a lower price on them. Second, switching to the new technology entails a higher level of risk and poor farmers are less able to insure against it. Indeed, GM corn cultivation offers higher yields than alternative varieties thanks to its better weed and pest management, which increases the gross return on land. At the same time, input costs also increase as seeds are more expensive and herbicide and fertilizer are used more intensively . These higher input costs imply larger potential losses in case of crop failure, which increase the riskiness of agricultural production. In a country exposed to many natural hazards like the Philippines (tropical cyclones, drought, flooding etc.), the probability of an adverse event destroying the harvest is not negligible. This is especially the case for smallholder farmers, who have limited options to insure against such shocks, either because they lack access to the formal financial sector or because their farm size restricts diversification options. Indeed, 45% of farms in the CAF 2012 only farm one plot, and an additional

33% only two. Moreover, heavy use of herbicide on GM corn prevents intercropping. As a result, large farmers who have easier access to financial institutions and alternative income sources are more able to insure against the increase in risk and therefore to reap the benefits from the new technology. In addition, the labor-saving characteristics of GM seeds favor the capital-rich individuals, which can increase income inequality between farmers.

While GM corn adoption was high at the end of our period, it was still not universal, especially in some parts of the country. In addition, the agricultural land market is likely to be slow to react to exogenous shocks given that farmers typically farm the same land every year. As a result, we may not be observing the full effect of the new technology, which does not necessarily imply that we only have a lower-bound effect. Indeed, if the optimal farm size becomes larger following the increase in productivity, adopters will expand their landholding compared to non-adopters, thus increasing land inequality. As adoption increases, new adopters also expand and we may therefore expect a decrease in inequality in a second time. Such a mechanism is, however, highly speculative and would need to be backed by empirical evidence.

One potentially important aspect that is overlooked in this paper is the implementation of the CARP land reform, which took place over the entire study period. This omission is the result of a complete lack of data regarding the amount of land redistributed at a disaggregated level. Given the high level of redistribution reported by the government, this may pose a threat to the validity of our results if landlords' opposition to the process was stronger in regions that benefited more from the new technology. However, given that the CARP started in the 90s, landlords would have needed to anticipate the arrival of the technology in order to keep their land until 2002. If this was the case, we would observe a similar effect between 1991 and 2002, which is not the case as reported in Table E.3. Such a political economy explanation is therefore unlikely to be driving our results. Moreover, the actual amount of land redistributed by the policy remains largely uncertain given that official statistics appear unrealistically high.

9 Conclusion

This paper shows that gains in corn productivity are an important factor explaining the evolution of land inequality in the Philippines during the first decade of the 21st century, following the introduction of genetically modified corn seeds. Our results show that municipalities that benefited more from this technology experienced an increase in landholding Gini and in the share of land occupied by the farms in the top decile. Several mechanisms and heterogeneous effects have been identified. First, the increase in land inequality appears to be driven by a smaller contraction of agricultural land in municipalities that were more affected. Second, the effect is stronger in places where agricultural credit transactions were widespread and improved seeds were less used in 1991. Third, the effect is heterogeneous across regions, although it is present on all major island groups. Fourth, it does not appear to be driven by migration between muncipalities or by rural-urban migration within municipalities. Fifth, it is not present in the decade preceding the introduction of GM corn.

This paper, however, is not meant to present any sort of welfare evaluation of GM corn. While land inequality is associated with a higher occurrence of terrorist activity, it is also positively correlated with income or expenditure data from household surveys and negatively correlated with poverty, although these correlations are not very robust. If the increased inequality has any welfare costs – which is not entirely supported by the data - , they are unlikely to outweigh the large benefits reported elsewhere on farm profits and household income.

While the empirical analysis uses an exogenous variation in profitability to identify the effect of the new technology, I lack agricultural data to go beyond the reduced-form equations and identify the mechanisms through which productivity affects the landholding distribution. Likewise, the agricultural land market is likely to be slow to react to exogenous shocks given that farmers typically farm the same land every year. As a result, we might only be observing the short-term effect of the commercialization of GM corn seeds. The identification of the mechanisms linking productivity to landholding inequality in the short and the long run offer an interesting avenue for future research.

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Appendix

A. Appendix A: Data cleaning details

A.1. Farm definition

The definition of a farm varies between the census waves. In 1991 and 2002, enumeration was limited to farms satisfying one of two conditions: (i) using at least 1000 square meters to raise crops, livestock or poultry and (ii) raising at least 20 heads of livestock or 100 heads of poultry. In 2012, however, this rule was lifted and any agricultural operation, regardless of land or herd size, was enumerated. Moreover, the rule does not appear to have been properly followed in 1991 as over one million farms report an area below 0.1 ha compared to only 8,355 in 2002. To make sure that temporal variations we find in the land distribution are not the result of changing farm definitions, farms with a total land area of less than 0.1 ha are excluded from the data. This implies dropping around 820,000 households in 2012. Through this restriction, we also make sure that the households considered devote a significant amount of resources to their farming activity, and we do not take into account all those who only tend a small plot of vegetables for their own consumption.

A.2. Use of PSGC

Tracking geographical units through time can be challenging if administrative boundaries change. The CAF raw data identifies the barangays (and the municipalities they are part of) using Philippine Standard Geographic Codes (PSGC). As administrative boundaries change, these codes are regularly updated, on average every two years. Unfortunately, the CAF documentation does not state clearly which version of the PSGC is used for each wave. In addition, the Philippine Statistics Authority was not able to provide a list of codes prior to 1998. I therefore use the version of PSGC that offers the highest number of matches, i.e. PSGC 1998 for the CAF 1991, the PSGC 2002 for the CAF 2002 and the PSGC 2018 for the CAF 2012. I was however unable to link 54 municipalities from the CAF 1991 to the rest of the data (representing 4.7% of the total agricultural area). Similarly, 3 and 1 municipalities had to be dropped from the CAF 2002 and CAF 2012 respectively.

To match municipalities across time, I use the PSGC 2002 version in order to minimize the distance with the other two. When municipalities merge or split between waves, I always use the larger entity for the analysis. Details of the PSGC matches are available upon request.

A.3. Crop area

In 1991 and 2002, the area planted in each crop is collected, along with the number of times that crop was planted. In 2012, however, we only know which crops were planted in each growing season. When several crops are cultivated on the same plot, we therefore do not know the area allocated to each one. In order to have consistent measures between years, I assume that when corn, rice or sugarcane are cultivated, they are planted on the entire plot. Given that they are rarely intercropped, this only leads to a slight overestimation of their prevalence. In addition, each crop is counted once, regardless of how many times it was harvested during the year. If a farmer grows rice during the wet season and corn during the dry season, his farm is included in the rice area as well as in the corn area. This implies that when we add the shares of land devoted to each crop, the result is likely to exceed one. Double counting of crops cultivated twice a year would lead to a stronger overestimation of their presence given that permanent crops such as coconut or banana are only counted once. Moreover, this measure is only used as a control variable in some regressions and the mismeasurement is unlikely to invalidate our main results.

For permanent crops such as coconut and banana, their dedicated area is very poorly reported and often missing. As many households own only a couple of trees, and they are much more likely to be intercropped, we would largely overestimate their presence by assuming that they cover the entire plot. The number of trees is however reported more reliably. I therefore use this information to recompute planted area by taking into account planting distance recommended by the Philippine Department of Agriculture. More specifically, I take planting densities of 123 plants/ha for coconut and 500 for banana (the median density in the 1991 data which contains both area and number of plants). In addition, the planted area is replaced by the plot area whenever it was larger.

A.4. Identification variables in CAF 2012

Respondents identification in the CAF 1991 and 2002 data are coherent and appear reliable, in the sense that it is possible to merge the different datasets with very limited loss of observations (only 20 unmatched plots in 1991 and less than 0.1% in 2002).

In the 2012 data, however, more cleaning is necessary in order to correclty match the different datasets. This is especially the case for the dataset containing plot-level tenure and use information. These variables are key to creating the land ownership inequality indicators used presented in Table 11. Agricultural operators are identified thanks to a series of ten identification variables (region, province, municipality, barangay, enumeration area, segment number, building serial number, housing unit serial number, household serial number and operator line). Manual inspection of those variables revealed that the last character of each entry was actually the first character of the following variable. For example, the farms located in the province of Abra report being in the region number 40 and the province number 10, while this province has the number 1 according to the PSGC. The same applies for all the subsequent identification variables. Correcting for this allows the matching of 98% of the observations. Removing the last digit of the household serial number to the unmatched variables increases the share of matched observations.

In addition to this problem with the id variables, the plotsizes reported in this dataset are rounded, for a reason that the PSA is not able to explain. As a result, 48% of the plots have a value of 0ha, which is problematic when computing land inequality indicators. This problem is solved using two methods.

First, when the plots have a match in another dataset (for example, containing crop information), the plotsize is taken from there. This allows me to confirm that the problematic values were indeed rounded. Second, for plots that cannot be matched, for example because they are left fallow or contain pasture land, the rounded value is kept and the 0 values are replaced by 0.1 ha, which is the average size of the matched plots that reported this value.

A.5. Sampling and weights recomputation

The sampling procedures for CAF 1991 and 2002 were the following:

1. Four provinces were fully enumerated (Laguna, Isabela, Bukidnon and Batanes). The province of Marinduque was also fully enumerated in 1991 only.
2. In the remaining provinces, the barangay with the largest farm area according to the previous census was enumerated with certainty.
3. In 1991, 50% of the remaining barangays were enumerated.
4. In 2002, the remaining barangays were divided into two groups: those sampled in 1991 and the others. 25% of each stratum was selected.

Comparing the last two waves is straighforward as we only keep data from the barangays surveyed in 2002 and use their weight on both waves.

When combining all three waves, or when comparing the 1991 and 2002 data, we need to take the sampling procedure into account in order to recompute the weights. Indeed, weights can change between census wave and the probability of being part of the full balanced panel depends on the weights in both waves. More specifically, we should not increase the weight given to certainty barangays since they were not randomly selected and therefore only represent themselves. The recomputed weight is therefore the average of the initial weights corrected by a factor γ_{ijt}:

$$w_{ij} = \frac{1}{2}\left(w_{ij91}\gamma_{ij91} + w_{ij02}\gamma_{ij02}\right),$$

with the correction factor γ_{ijt} equal to 1 for the certainty barangays and to $\frac{N_{j91}}{\Sigma_i w_{ij91}}$ otherwise, where N_{jt} corresponds to the number of barangays enumerated in municipality j in year t.

Appendix B: Inequality decomposition

The general formula of GE measures is given by

$$GE(\alpha) = \frac{1}{\alpha(\alpha-1)} \left[\frac{1}{N} \sum_{i=1}^{N} \left(\frac{x_i}{\bar{x}} \right)^{\alpha} - 1 \right],$$

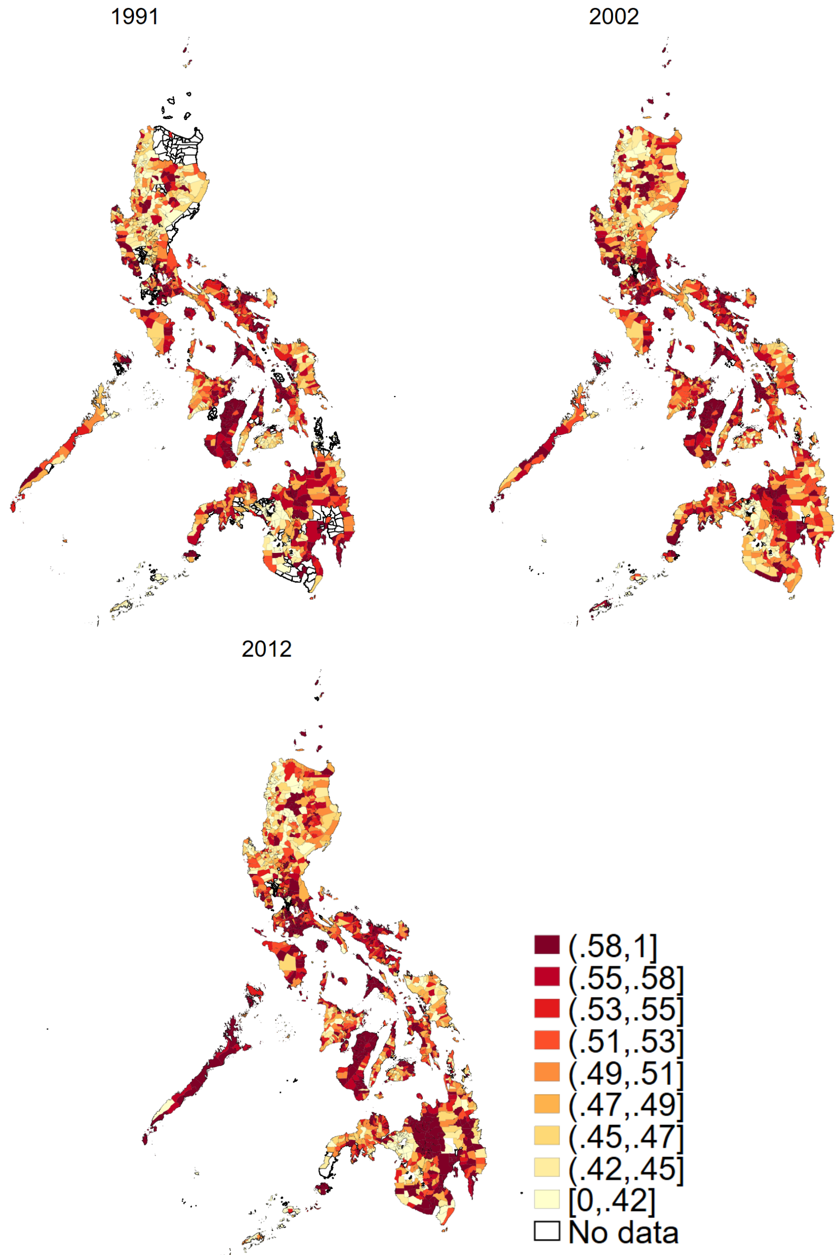
where x_i is the landholding size and $\bar{x}$ the mean farm size. The parameter α represents the weight given to land size differences along the farm size distribution, a low value giving more weight to the left tail of the distribution while a high value giving more weight to the right tail. The two most used values are 0 and 1, respectively giving Theil's L and Theil's T indices. These indicators can then be decomposed into two additive components, measuring between-municipality and within-municipality inequality. For Theil's T, this first decomposition is given by

$$\begin{aligned} T &= \frac{1}{N} \sum_{i=1}^{N} \frac{x_i}{\bar{x}} ln \left(\frac{x_i}{\bar{x}} \right) \\ &= \sum_{i=1}^{N} \frac{x_i}{X} ln \left(\frac{x_i N}{X} \right) \\ &= \sum_{j} \left(\frac{X_j}{X} \right) T_j + \sum_{j} \left(\frac{X_j}{X} \right) ln \left(\frac{X_j/X}{N_j/N} \right), \end{aligned}$$

where municipalities are indexed by j and T_j is the value of Theil's T index computed for municipality j[34]. It is also possible to decompose this measure along more than one level, provided that each level is nested within the other. This analysis is only possible for 2012 as it requires information on the full census of barangays. Following Akita (2003), I therefore decompose national inequality into three components: between municipality, between barangay and within barangay and report the results in Table 2.

[34] Theil's L index decomposes similarly, using the number of farms N as weights. For more information, see Haughton and Khandker (2009).

Appendix C: Spatial distribution of landholding Gini



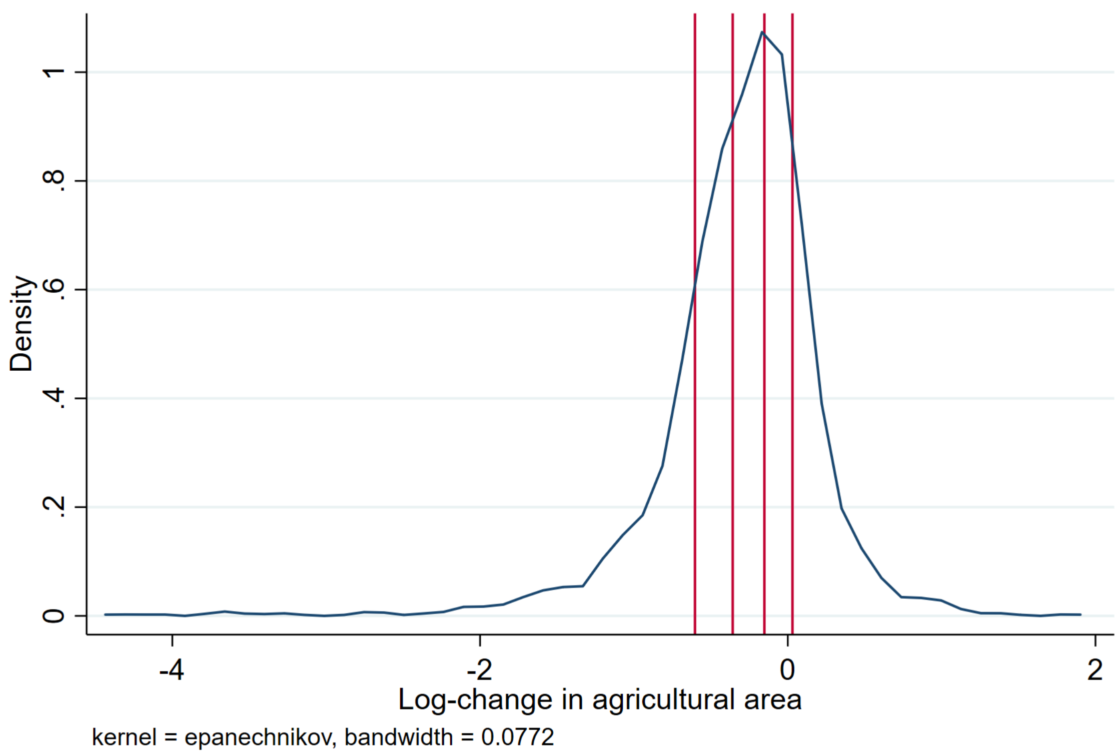
Appendix D: Supplementary material - Results

Table D.1: Top decile share and productivity change - Mechanisms

VARIABLES	(1)	(2)	(3)	(4)
Potential gain from GM corn	0.554**	0.435*	0.535**	0.117
	(0.239)	(0.239)	(0.234)	(0.209)
Municipality area (Log)	1.212***	0.865**	1.255***	0.573*
	(0.346)	(0.356)	(0.346)	(0.310)
1991 Ag area (Share)	2.737**	2.122**	2.915***	2.275**
	(1.104)	(1.071)	(1.109)	(0.975)
1991 Corn share	1.436	2.048*	1.352	2.498**
	(1.191)	(1.154)	(1.185)	(1.013)
1992 Night lights (Log)	0.418**	0.725***	0.332	0.665***
	(0.203)	(0.205)	(0.210)	(0.202)
Δ Farm area (Log)		4.604***		12.075***
		(0.897)		(1.123)
Δ Nb farms (Log)			-1.699**	-10.978***
			(0.765)	(1.142)
Observations	1,434	1,434	1,434	1,434
R-squared	0.023	0.084	0.030	0.230

Dependent variable is the change in land share occupied by the top decile of the landholding distribution, between 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low leve and ls of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure D.1: Distribution of the change in agricultural area (Log)



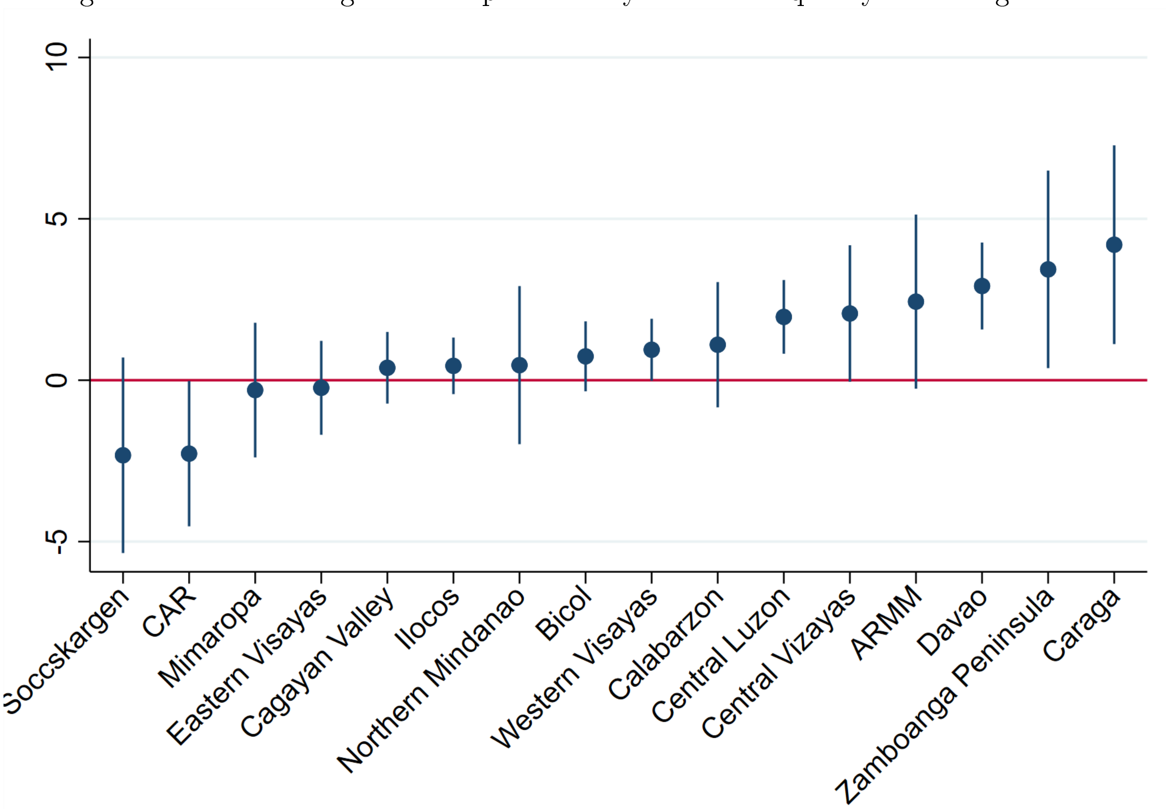
Vertical lines indicate quintiles

Table D.2: Effect of agricultural area on the productivity-inequality relationship

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Potential gain from GM corn	0.457**	0.314	0.168	0.168	0.259	0.260	0.347*	0.464**
	(0.208)	(0.207)	(0.207)	(0.205)	(0.204)	(0.205)	(0.203)	(0.202)
Municipality area (Log)	1.080***	0.648**	0.547*	0.480	0.598**	0.686**	0.790***	0.993***
	(0.301)	(0.304)	(0.303)	(0.297)	(0.297)	(0.293)	(0.290)	(0.291)
1991 Ag area (Share)	3.676***	3.080***	3.544***	3.529***	3.536***	3.805***	3.758***	3.733***
	(0.965)	(0.950)	(0.959)	(0.919)	(0.910)	(0.916)	(0.900)	(0.914)
1991 Corn share	0.553	1.024	1.286	1.514	1.617	1.559	1.462	1.227
	(1.037)	(1.025)	(1.018)	(1.000)	(0.987)	(0.988)	(0.987)	(0.996)
1992 Night lights (Log)	0.358**	0.546***	0.606***	0.603***	0.615***	0.581***	0.515***	0.470***
	(0.180)	(0.180)	(0.179)	(0.177)	(0.176)	(0.176)	(0.174)	(0.175)
Quintile 1 Δ Ag area (Log)		-4.867***	-5.898***	-7.126***	-9.293***			
		(0.639)	(0.659)	(0.699)	(0.825)			
Quintile 2 Δ Ag area (Log)			-3.920***	-5.134***	-7.318***			
			(0.498)	(0.550)	(0.705)			
Quintile 3 Δ Ag area (Log)				-3.540***	-5.745***	2.537***		
				(0.522)	(0.685)	(0.530)		
Quintile 4 Δ Ag area (Log)					-4.396***	3.877***	2.962***	
					(0.695)	(0.548)	(0.489)	
Quintile 5 Δ Ag area (Log)						8.280***	7.388***	6.627***
						(0.679)	(0.633)	(0.613)
Observations	1,436	1,436	1,436	1,436	1,436	1,436	1,436	1,436
R-squared	0.025	0.073	0.104	0.126	0.152	0.147	0.135	0.118

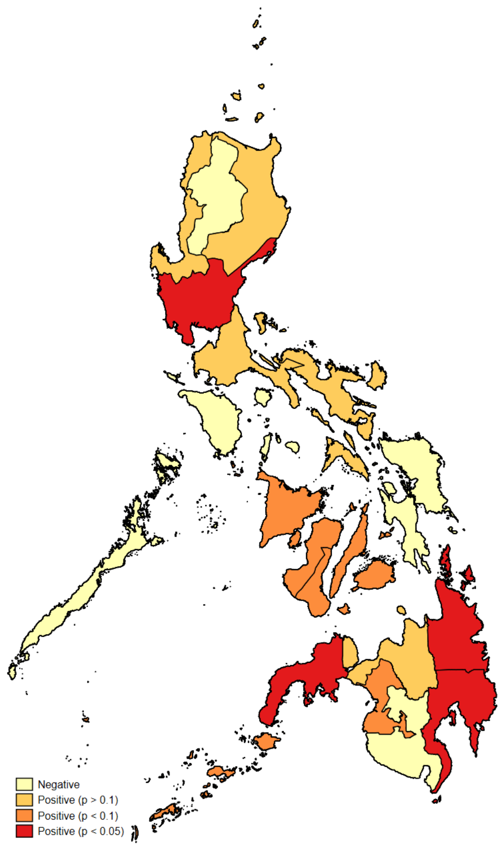
Dependent variable is the change in landholding Gini between 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure D.2: Effect of agricultural productivity on land inequality at the regional level



Each point represents the coefficient of the interaction between the potential gain from GM corn and the region dummy, using the change in landholding Gini as dependent variable.

Figure D.3: Effect of agricultural productivity on land inequality at the regional level



Map color reflects the sign and significance of the coefficients reported in Figure D.2.

Appendix E: Supplementary material - Robustness tests

Table E.1: Landholding Gini and productivity change - controlling for population and economic development

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Potential gain from GM corn	0.459**	0.640***	0.488**	0.430**	0.426**	0.414**	0.430**
	(0.210)	(0.212)	(0.198)	(0.207)	(0.208)	(0.208)	(0.193)
Municipality area (Log)	1.074***	0.819***	0.868***	1.057***	1.047***	1.099***	0.917***
	(0.301)	(0.302)	(0.295)	(0.302)	(0.301)	(0.300)	(0.296)
1991 Ag area (Share)	3.624***	2.551***	2.913***	3.606***	3.634***	3.475***	2.807***
	(0.964)	(0.967)	(0.916)	(0.974)	(0.971)	(0.936)	(0.923)
1991 Corn share	0.540	-0.336	-1.516	0.600	0.557	0.680	-1.408
	(1.044)	(1.020)	(0.935)	(1.046)	(1.052)	(1.045)	(0.940)
1992 Night lights (Log)	0.362**	0.282	0.446**	0.388**	0.373**	0.371**	0.512***
	(0.183)	(0.181)	(0.176)	(0.196)	(0.186)	(0.182)	(0.190)
Δ Corn (share)		-14.706***	-9.695***				-10.054***
		(3.001)	(2.774)				(2.780)
Δ Population (Log)				-0.845			-2.379
				(2.357)			(2.162)
Δ Rural pop (Share)					-2.043		-3.201
					(9.620)		(8.909)
Δ Night light (Log)						0.885*	0.793*
						(0.469)	(0.420)
Observations	1,434	1,434	1,434	1,424	1,424	1,433	1,423
R-squared	0.025	0.058	0.223	0.025	0.025	0.028	0.226
Crop shares	NO	NO	YES	NO	NO	NO	YES

Dependent variable is the change in landholding Gini coefficient between 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. Crop shares include the change in agricultural land share of rice, sugarcane, coconut, banana, other temporary and other permanent crops. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E.2: Landholding Gini and productivity change - Topo-geographical controls

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GM corn	0.459**	0.794***	0.828**	0.612***	0.403
	(0.210)	(0.238)	(0.372)	(0.216)	(0.284)
Municipality area (Log)	1.074***	0.959***	1.023***	1.044***	-0.418
	(0.301)	(0.307)	(0.304)	(0.302)	(0.409)
1991 Ag area (Share)	3.624***	3.955***	3.901***	2.603***	1.560
	(0.964)	(0.952)	(0.965)	(0.980)	(1.338)
1991 Corn share	0.540	0.066	0.439	-0.327	0.743
	(1.044)	(1.033)	(1.040)	(1.121)	(1.539)
1992 Night lights (Log)	0.362**	0.348*	0.373**	0.404**	0.166
	(0.183)	(0.184)	(0.182)	(0.184)	(0.232)
Elevation		0.003**			
		(0.001)			
Ruggedness			0.027		
			(0.021)		
Longitude				0.364*	
				(0.197)	
Latitude				-0.059	
				(0.121)	
Observations	1,434	1,434	1,434	1,434	1,432
R-squared	0.025	0.032	0.027	0.031	0.186
Province FE	NO	NO	NO	NO	YES

Dependent variable is the change in landholding Gini coefficient between 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E.3: Placebo test using 1991 and 2002 data

VARIABLES	(1)	(2)	(3)	(4)
	Δ Gini		Δ Top 10%	
Potential gain from GM corn	-0.228	0.128	-0.289	-0.014
	(0.174)	(0.199)	(0.190)	(0.227)
Municipality area (Log)		-1.205***		-1.298***
		(0.295)		(0.345)
1991 Ag area (Share)		-8.918***		-6.725***
		(1.405)		(1.737)
1991 Corn share		3.723***		4.405***
		(0.901)		(0.953)
1992 Night lights (Log)		-0.265		-0.343
		(0.198)		(0.225)
Observations	1,350	1,341	1,350	1,341
R-squared	0.001	0.051	0.002	0.033

Changes in dependent variables are calculated over the years 1991 and 2002. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E.4: Productivity change and landholding inequality - Including CAF 1991

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
		Δ Gini			Δ Top 10%	
Potential gain from GM corn	-0.228	-0.077		-0.289	-0.119	
	(0.174)	(0.185)		(0.190)	(0.206)	
Potential gain from GM corn * 2012	0.758***	0.651**	0.750**	0.872***	0.722**	0.861**
	(0.259)	(0.260)	(0.310)	(0.286)	(0.286)	(0.345)
Municipality area (Log)		-0.001			0.015	
		(0.216)			(0.250)	
1991 Ag area (Share)		-1.248			-0.996	
		(0.817)			(0.954)	
1991 Corn share		2.052***			2.851***	
		(0.706)			(0.782)	
1992 Night lights (Log)		0.053			0.045	
		(0.137)			(0.153)	
Observations	2,870	2,775	2,674	2,870	2,775	2,674
R-squared	0.004	0.007	0.315	0.004	0.008	0.315
Year FE	YES	YES	YES	YES	YES	YES
Municipality FE	NO	NO	YES	NO	NO	YES

Changes in dependent variables are calculated over the years 1991, 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E.5: Spatial correlation correction

		(1)	(2)	(3)	(4)
		Δ Gini		Δ Top 10%	
Potential gain from GM corn		0.526	0.442	0.591	0.520
	Robust SE	[0.006]	[0.029]	[0.007]	[0.020]
	Conley 25-km radius	[0.026]	[0.073]	[0.039]	[0.078]
	Conley 50-km radius	[0.053]	[0.113]	[0.080]	[0.124]
	Province cluster	[0.044]	[0.096]	[0.061]	[0.084]
Observations		1,520	1,434	1,520	1,434
R-squared		0.006	0.026	0.006	0.025
Controls		NO	YES	NO	YES

Changes in dependent variables are calculated over the years 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the municipality.
P-values between brackets.

Controls include log of municipality area, change in the share of land devoted to agriculture, change in the share of agricultural land devoted to corn and log change of night light intensity.

Table E.6: Barangay-level analysis

	(1)	(2)	(3)	(4)	(5)	(6)
		Δ Gini			Δ Top 10%	
VARIABLES	All barangays	Balanced panel	Rural barangays	All barangays	Balanced panel	Rural barangays
Potential gain from GM corn	0.610***	0.626***	0.819***	0.368***	0.209	0.409**
	(0.120)	(0.174)	(0.186)	(0.108)	(0.164)	(0.170)
Barangay area (Log)		0.347	0.473**		-0.215	-0.042
		(0.215)	(0.239)		(0.210)	(0.231)
1991 Ag area (Share)		-0.020	-0.026**		0.005	0.009
		(0.015)	(0.012)		(0.006)	(0.006)
1991 Corn share		0.302	0.395		1.071	1.187*
		(0.729)	(0.725)		(0.698)	(0.711)
1991 Night lights (Log)		0.604	1.149		0.746	0.779
		(0.980)	(1.163)		(0.680)	(0.970)
Observations	11,905	6,767	5,439	11,905	6,767	5,439
R-squared	0.004	0.005	0.009	0.002	0.003	0.003

Changes in dependent variables are calculated over the years 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with high and low levels of inputs from the FAO-GAEZ. The unit of observation is the barangay.
Robust standard errors clustered at the municipality-level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E.7: Alternative measures of potential gain from GM corn

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Intermediate - Low Inputs				High - Intermediate Inputs			
VARIABLES	Δ Gini		Δ Top 10%		Δ Gini		Δ Top 10%	
Potential gain from GM corn	1.304*	0.831	1.500*	1.173	0.742***	0.679***	0.806***	0.796***
	(0.762)	(0.827)	(0.892)	(1.002)	(0.241)	(0.263)	(0.267)	(0.294)
Municipality area (Log)		0.983***		1.116***		1.095***		1.231***
		(0.301)		(0.348)		(0.301)		(0.345)
1991 Ag area (Share)		3.898***		3.027***		3.560***		2.679**
		(0.963)		(1.103)		(0.961)		(1.101)
1991 Corn share		0.412		1.298		0.573		1.466
		(1.040)		(1.185)		(1.044)		(1.193)
1992 Night lights (Log)		0.440**		0.505**		0.338*		0.395*
		(0.180)		(0.200)		(0.182)		(0.202)
Observations	1,520	1,434	1,520	1,434	1,520	1,434	1,520	1,434
R-squared	0.003	0.023	0.003	0.020	0.007	0.026	0.006	0.024

Dependent variable is the change in landholding Gini coefficient between 2002 and 2012. Potential gain from GM corn is the difference between potential rainfed corn yield with intermediate and low levels of inputs in columns 1-4 and between high and intermediate in columns 5-8. The unit of observation is the municipality.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix F: Supplementary material - Socio-economic outcomes

Table F.1: Income, expenditure and employment for farming sample

VARIABLES	(1) Income	(2) Expenditure	(3) Head employed	(4) Poor	(5) Bottom quintile	(6) Top decile
PANEL A - WITHOUT MUNICIPALITY CONTROLS						
Past Land Gini	0.063	0.121	0.275***	0.040	0.036	0.031
	(0.115)	(0.109)	(0.075)	(0.070)	(0.069)	(0.024)
Land Gini	0.254**	0.278***	0.474***	-0.170***	-0.162**	0.020
	(0.103)	(0.098)	(0.064)	(0.063)	(0.063)	(0.016)
Observations	38,624	38,624	38,624	38,624	38,624	38,624
R-squared	0.489	0.528	0.111	0.228	0.211	0.121
HH controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality controls & FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
PANEL B - WITH MUNICIPALITY CONTROLS						
Past Land Gini	0.043	0.057	0.030	0.039	0.046	0.024
	(0.132)	(0.119)	(0.120)	(0.096)	(0.089)	(0.030)
Land Gini	-0.023	0.071	0.010	-0.007	0.025	-0.010
	(0.141)	(0.123)	(0.105)	(0.114)	(0.105)	(0.028)
Potential corn yield	-0.015*	-0.011	-0.017***	0.011**	0.008	0.000
	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)	(0.002)
Observations	38,623	38,623	38,623	38,623	38,623	38,623
R-squared	0.610	0.659	0.215	0.362	0.351	0.161
HH controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality controls & FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Data from the FIES 2003 and FIES 2012. For households observed in 2003 and 2012, past land Gini corresponds to the landholding Gini index computed at the municipality level in 1991 and 2002 respectively. Land Gini corresponds to the landholding Gini index computed at the municipality level in 2002 and 2012 respectively.
Columns 1 and 2 use per capita log income or expenditure. Columns 3-6 use dummy variables as dependent variables.
Household control variables include household head's gender, age, education level and household size. Municipality control variables include the log of farm number and of agricultural area.
Robust standard errors clustered at the municipality level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix G: Supplementary material - Terrorist activities

Figure G.1: Spatial distribution of terrorist activity between 1991 and 2018

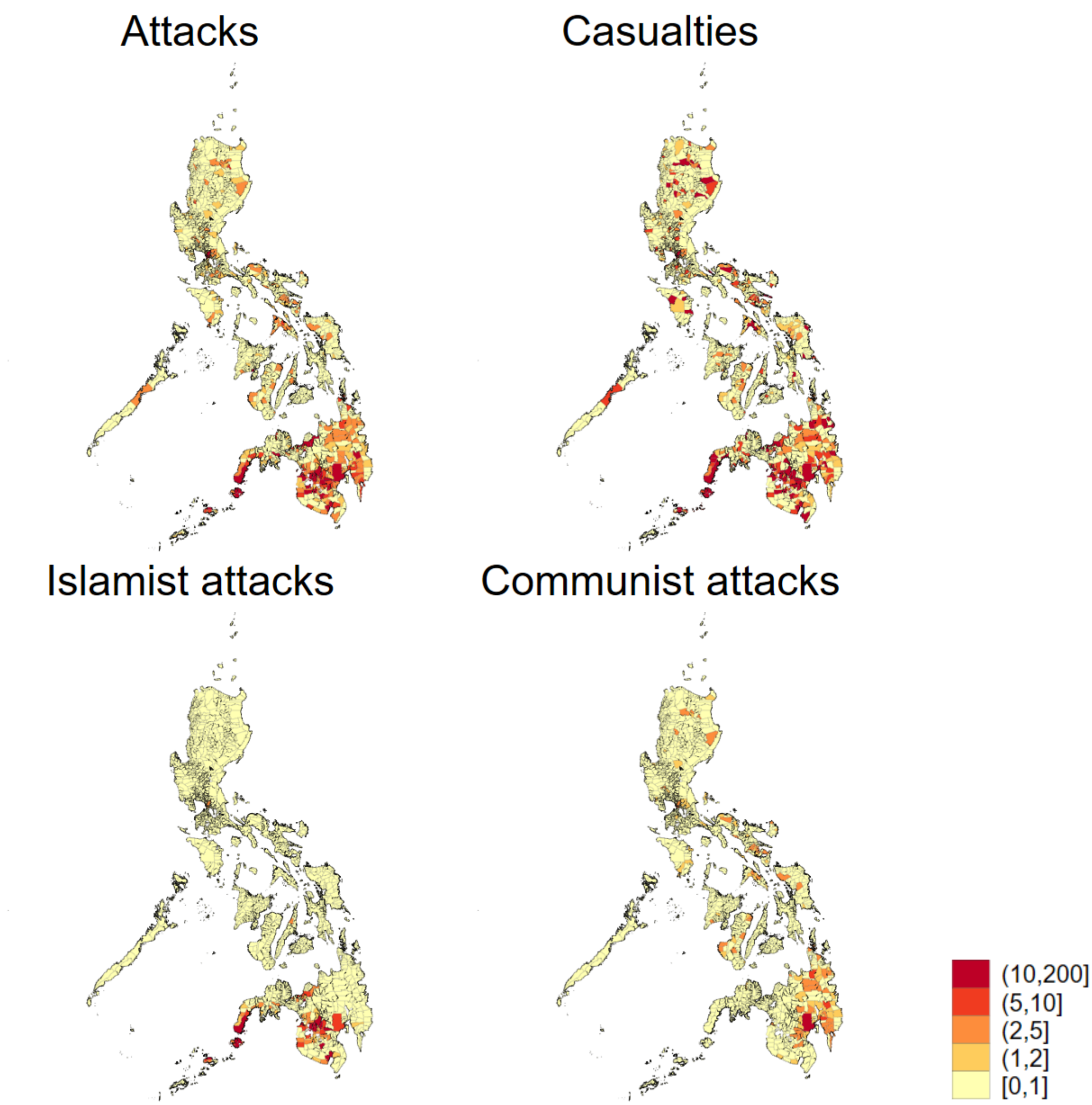


Table G.1: Terrorist attack casualties

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All		Islamist		Communist	
Land Gini	4.204**	3.523**	5.050*	7.268**	2.184	2.785
	(1.789)	(1.602)	(2.862)	(2.925)	(1.969)	(2.296)
Observations	28,857	7,454	7,002	1,423	23,351	3,596
Year FE	YES	YES	YES	YES	YES	YES
Province time trend	YES	NO	YES	NO	YES	NO
Municipality FE	NO	YES	NO	YES	NO	YES
Land Gini	2.162	3.325***	2.658	4.485	1.228	3.273
	(2.088)	(1.079)	(3.123)	(2.805)	(2.007)	(2.612)
Log Agricultural land	0.344*	-0.406***	0.248	-1.143***	0.313	0.066
	(0.190)	(0.152)	(0.323)	(0.386)	(0.216)	(0.297)
Log Night light	0.425***	-0.293**	0.491***	-0.369	0.102	-0.357*
	(0.082)	(0.137)	(0.152)	(0.293)	(0.102)	(0.192)
Observations	28,848	7,454	7,000	1,423	23,343	3,596
Year FE	YES	YES	YES	YES	YES	YES
Province time trend	YES	NO	YES	NO	YES	NO
Municipality FE	NO	YES	NO	YES	NO	YES

Poisson pseudo-maximum likelihood with fixed effects regressions. Unit of observation is the municipality, each municipality is observed every year between 1991 and 2012.
Robust standard errors clustered at the provincial level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$