The Impact of Uncertainty in Agriculture*

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Abstract

Income uncertainty in the rural economy is widely considered an important impediment to growth in poor countries. This paper uses a rich dataset on productivity, land use, and output for 17 different crops across 500,000 plots of land in 87 countries to study the impact of uncertainty in the agricultural sector. The analysis relies on historical variability in crop productivity driven by local climatic conditions to estimate the impact of uncertainty on farmers' land allocation. Applying a standard portfolio framework, we estimate that the incentive to diversify led to large losses in agricultural revenue. We adopt a spatial regression discontinuity approach that compares how national institutions affected agricultural outcomes near the borders of former British and French colonies in Africa. We find that farmers in former British colonies, which tended to adopt pro-private sector policies, adopted more advanced input technologies and achieved higher crop-specific returns. In contrast, farmers in former French colonies, which tended to devote more public resources to the agricultural sector, tolerated higher levels of uncertainty and adopted more specialized crop portfolios. These offsetting effects suggest that both a well-functioning market system along with public investments that reduce risk may be necessary to foster rural economic development.

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1 Introduction

Households in many rural areas are subject to substantial economic uncertainty. Recurrent droughts and fluctuations in output prices lead to volatile agricultural earnings (e.g., Carter, 1997; Shanahan et al., 2009), and rural producers often lack access to credit or insurance markets (Binswanger and Rosenzweig, 1986).[1] Despite a growing literature, there is little consensus on the impact of uncertainty on the rural economy, and estimated effects have varied widely across different locations.

This paper combines a detailed micro-dataset on agricultural productivity, land use, and output to study the economic impact of agricultural income uncertainty at a global scale. Our analysis builds on the simple idea that risk-averse farmers facing *ex ante* uncertainty over future revenue may sacrifice additional earnings in order to reduce exposure to income volatility. If climate shocks and output price shocks affect all crops similarly, there would be no scope for crop portfolio adjustments to lower income uncertainty. However, to the extent that output price shocks and climatic conditions are crop specific, farmers may divert land to crops that generate lower expected returns but help smooth against annual income fluctuations.

Our empirical analysis is based on detailed geospatial data assembled by the Global Agro-Ecological Zones (GAEZ) project of the Food and Agriculture Organization (FAO). The GAEZ project provides agronomic modelling with high-resolution data to provide information on potential yields, harvested land, and actual yields by crop for 1.7 million plots of land that span the earth's surface.[2] Potential crop yields are constructed by combining agronomic models of specific crop requirements with high-resolution data on geographic and climatic conditions. Crucially, the GAEZ data provides information potential crop yields by year, allowing us to construct measures of mean and variability in yields by crop for each grid cell, whether or not the crop is actually grown.

[1] For example, Kazianga and Udry (1996) find that the standard deviation of rainfall-induced income variation is more than half of average rural household income in Burkina Faso.

[2] Land plots are available at the 5-arc-minute level, which corresponds to roughly 10 km by 10 km at the equator.

To estimate the impact of uncertainty on rural producers decision-making, we combine the GAEZ crop data with a standard mean-variable portfolio framework (Markowitz, 1952). Farmers are assumed to trade-off higher expected crop returns against increased variance on their plot. We combine this simple framework with plot-level data on the observed land allocation, expected returns by crop, and the historical covariance in crop yields to calculate the mean-variance efficient (MVE) frontier for each plot of land: the maximum attainable return given a specific level of output risk. The empirical analysis compares farm earnings under full specialization, the MVE allocation, and the actual allocation to calculate the fraction of revenue losses attributable to diversification incentives across each plot of agricultural land. Farmers may divert land from the highest yield crop for a variety of motives unrelated to output risk. Our identification, which relies on the specific structure of the covariance matrix in crop returns, allows us to the effect of uncertainty from other sources of land misallocation.

We have three main findings. First, 'crop misallocation' – the fact that farmers did not specialize in revenue maximizing crops – is associated with large losses in agricultural revenue. We estimate that revenue on the typical plot could have been doubled under full specialization. These losses exceeded those attributable to within-crop distortions, and they were particularly large in lower income countries. Crop misallocation cannot be explained by the selection of workers into the agricultural sector (Lagakos and Waugh, 2013), distortions affecting the scale of production units in agriculture (e.g., Adamopoulos and Restuccia, 2014), or farmers' choices of input technologies (e.g., Donovan, 2016), since each of these factors will have similar effects on agricultural productivity irrespective of the particular crop that is grown.

Second, we find that the incentive to diversify land against annual income uncertainty was the primary source of crop misallocation. Comparing the MVE efficient allocation to the observed land allocation and the allocation under full specialization, we calculate that 80 percent of the losses from crop misallocation are attributable to diversification incentives. Farmers in richer and poorer countries faced similar level of income uncertainty. Nevertheless, their response was markedly different. Farmers in below-median income countries planted more different crops and devoted 20 percent less agricultural land to the dominant crop. Comparing the sources of crop misallocation across countries, we estimate that the losses attributable to income uncertainty were 50 percent larger in countries with below-median income. Together, these findings suggest that rural income uncertainty is a major source of revenue losses in poorer countries, and that limited access to insurance and incomplete credit markets may be an important reason why agricultural productivity is so low in poor countries.

Third, using a regression discontinuity design, we find no significant difference in overall agricultural output across African farmers operating at the borders of former British and French colonies. These small overall effects mask two offsetting forces. On the one hand, farmers in former British colonies used more advanced input technologies and achieved higher crop-specific returns. On the other hand, these farmers were more likely to diversify their crop portfolio given a particular level of economic uncertainty. We argue that these findings are consistent with the institutional arrangements of the two sets of countries. In particular, former British colonies were more likely to adopt pro-private sector policies, and better functioning credit markets, which may have faciliated investment in the agricultural sector. In contrast, former French colonies had larger public sectors that devoted more resources to the agricultural sector, potentially shielding rural producers from the consequences of income volatility. Together, the findings suggest that both a well-functioning market systems along with some form of non-market interventions that reduce individual exposure to uncertainty may be necessary to foster rural economic development.

The paper contributes to the large literature on the role of uncertainty in agriculture. Researchers have identified a number of channels through which individual households cope with income uncertainty in the face of credit constraints, including precautionary savings (Deaton, 1990, 1991; Fafchamps et al., 1998), remittances from urban family members (Rapoport and Docquier, 2006; Gonzalez-Velosa, 2012, Yang and Choi, 2007), delayed technological adoption (Antle and Crissman, 1990, Dercon and Christiaensen, 2011, Donovan, 2014), and crop diversification (Kurosaki, and Fafchamps, 2002; Di Falco, and Chavas, 2009, Nicola, 2015). Despite this research, there is ongoing debate of the effectiveness of these strategies (Udry, 2016). The lack of consensus is, in part, a result of the fact that the populations studied differ widely in both the risks posed by climatic shocks and the institutional framework in which rural producers operate. By studying the consequences of income uncertainty across virtually all cultivated land, we are able to examine the impact of income uncertainty in agriculture at a much broader scale, allowing us to explore the extent to which different levels of producer risk and different income levels impact decision-making in rural areas.

This paper also contributes to the literature that studies agricultural productivity gaps and their role in explaining cross-country income differences. A number of studies have documented the role of sector specific distortions for agricultural productivity (Adamopoulos and Restuccia, 2011; Restuccia, Yang, and Zhu, 2008; Tombe, 2014; Adamopoulos, 2011). Researchers have also examined role of self-selection across sectors in explaining these large gaps (Lagakos and Waugh, 2013). Our results complement recent work by Donovan (2014) that shows how idiosyncratic risk can lead to underinvestment in the agricultural sector. Most closely related to our work is Adamopoulos and Restuccia (2015), who use the GAEZ data to explore the extent to which agricultural productivity gaps are driven by production inefficiencies, crop misallocation, and production inefficiencies across cultivated and cultivatable plots. Consistent with our results, they find that the majority of cross-country differences in output can be attributed to economic decision-making rather than differences in land quality.

Our analysis also contributes to a growing literature that uses the historical partition of African countries to study the impact of national institutions on economic outcomes. Previous research has found mixed evidence on the importance of institutions (e.g., Michalopoulos and Papiaoannou, 2013, 2014).[3] Our results show that the limited overall impact on rural economic activity was partly a reflection of offsetting institutional arrangements. In particular, the benefits the pro-market institutions that promoted rural investment were counteracted by the redistributive policies that developed in former French colonies.

[3]Other research that exploits border discontinuities to identify the role of particular national policies include Miguel (2004), Cogneau and Moradi (2011), Bubb (2012), and Cogneau, Mesplé-Somps, adn Spielvogel (2012).

2 Data

2.1 Crop Productivity, Agricultural Output, Land Use, and Prices

We obtain information on crop productivity, agricultural output and land use from the Global Agro-Ecological Zones (GAEZ) project, which is organized under the Food and Agriculture Organization's (FAO) and the Institute for Applied Systems Analysis. Information on country-level agricultural prices is obtained from the FAO.

The GAEZ project provides estimates of crop productivity by combining information on geographic and climatic conditions at the grid cell level with state-of-the art agronomic models of how each crop will respond to these conditions. The GAEZ productivity estimates are available for every plot and for every crop, regardless of whether the crop is actually grown. Crop productivity estimates are calcuated based on a large number of plot growing characteristics. Invariant characteristics include eight different soil types, elevation, and land gradient. Climatic variables include rainfall, temperature, humidity, wind speed, and sun exposure. The GAEZ project is particularly careful in its treatment of weather conditions. Annual crop productivities are derived based on an aggregation of daily weather conditions, and the model captures how potential yields of each crop are affected by weather conditions throughout the growing cycle. Given the large variability climatic conditions, crop productivity is calculated in every year and for the entire "baseline" period from 1961 to 1990.

These plot characteristics are combined with a vector of hundreds of crop-specific parameters that capture how the output of each crop responds to environmental conditions. The parameter estimates are taken from the agronomic literature, and are typically established through field experiments at agricultural research stations. Because output on a plot of land depends on farmers decisions over inputs, such as irrigation, fertilizers, machinery, and labor, the GAEZ project calculates different potential productivity estimates depending on the choice of inputs. In our analysis we focus on potential productivity from "rain-fed" water supply systems, which account for more than 85 percent of agricultural land. Because we are interested in the maximum attainable yields on a plot of land, the analysis is based on potential yields under "high input" production technologies. The GAEZ project defines "high input" technologies as market oriented farm management that is fully mechanized with low labor intensity, adopts fallow and conservation measures, uses high yielding seed varieties, and uses optimum applications of nutrients and chemical pest, disease, and weed control.[4] Potential crop productivity are assembled at the 5-arc-minute level, which corresponds to roughly 10 km by 10 km grid cells at the equator. The size of the grid cells is determined by the climatic data, which are available at the 5-arc-minute level. We measure potential crop production, $A^k_{i,t}$, as potential output per hectare for each of the ten staple crops, k, on a plot of land i, in year t.

The GAEZ project also provides information on cultivated land and actual yields for every crop in 2000. These data are assembled at the 5 arc-minute level using information drawn from several different sources. First, GAEZ combines several global studies of land cover to categorize land use at the grid cell level.[5] Second, local measures of agricultural crop production are compiled from Monfreda et al. (2008). The Monfreda et al. (2008) dataset provides information on crop yields and cultivated area by crop for a 150 countries at sub-national political units, and 19,751 political units two levels below the country. Figures 1 presents the map of political units from Monfreda et al. (2008). High resolution statistics were widely available in areas of active agricultural production, whereas the larger political units typically covered regions that were unsuitable for cultivation. The GAEZ project combines the two data sources with downscaling methods to derive spatial distributions of agricultural activity that are consistent with both the local data from remote sensing and the agricultural production statistics.[6] For every grid cell, the GAEZ project provides information on agricultural production and land use

[4]We also explore the sensitivity of the findings to production under "low input" technologies – traditional farm management that is largely subsistence with labor intensive techniques, and no use of chemicals for pest control and minimal soil conservations measures.

[5]Land use is categorized as follows: i) rain-fed cultivation, ii) irrigated cultivation, iii) forest, iv) pasture and other vegetated land, v) barren and sparsely vegetated land, vi) water, and vii) urban and land required for housing and infrastructure.

[6]We explore the sensitivity of the results to excluding countries for which agricultural data is available at higher levels of aggregation.

for each crop. Specifically, $Q^k_{i,2000}$ measures total output (measured in dry-weight tons) of crop k on plot i for each of the 10 crops used in the analysis. We denote $L_{i,2000}$ as the total hectares of cultivated land on plot i, and $s^k_{i,2000}$ the fraction of land devoted to crop k.

Data on agricultural producer prices are obtained from the FAOSTAT program at the FAO (available at http://faostat3.fao.org/home/E). We assemble data on real output prices, $p^k_{c,t}$, for each crop, k, in a country, c, in year t.[7] Each grid cell observation is matched to relevant country prices based on the country in which it falls using the country boundaries file available from the World Borders Dataset (Thematic Mapping).[8]

The analysis is based on roughly 500,000 grid cells that had positive land used in agriculture in 2000.[9] Table 1 reports the crops and countries used in the analysis. We consider 17 staple crops that comprise almost two-thirds of arable land worldwide.[10] Our primary sample accounts for almost two thirds of global land devoted to these crops, and spans 87 countries.[11]

2.2 Variable Construction

We combine the GAEZ data to assemble various measures of agricultural activity at the plot level. These variables are used to compare observed farm earnings to potential earnings, given land and climatic conditions.

We calculate total agricultural revenue per plot in 2000 (M4). For each grid cell, we use information on output per hectare for each crop, $Q^k_{i,2000}$, total cultivated land, $L^k_{i,2000}$, the share of land devoted to each crop, $s^k_{i,2000}$, and crop output prices, $p^k_{c,2000}$ to calculate actual plot

[7] All prices are inflation-adjusted (DISCUSS).

[8] For the small number of observations that span multiple country boundaries, we assign the country based on the grid cell centroid.

[9] The full GAEZ dataset consists of 2.2 million grid cells. We omit roughly 1.5 million plots that had zero agricultural production. A further 200,000 plots are excluded because of missing information on crop output prices.

[10] Virtually all remaining arable land is devoted to fodder and vegetable production.

[11] China and Russia account for roughly half of the remaining arable land. These two countries are excluded from the main analysis because of missing information on historical crop output prices, although we explore the robustness of the results to their inclusion.

revenue in 2000 as follows:

$$M4_{i,2000} = L_{i,2000} \cdot \sum_k p^k_{c,2000} \cdot Q^k_{i,2000} \cdot s^k_{i,2000}.$$

The second variable of interest is potential revenue, $M3_{i,t}$. This variable is constructed by holding total agricultural land and crop land shares fixed at their 2000 values, and assuming that farmers achieved maximum attainable yields per hectare for every crop, k grown, A_{kit}, in year t. The gap between actual revenue and potential revenue reflects the losses in agricultural revenue attributable to farmers not maximizing output on a particular plot of land.[12] We calculate potential revenue in every year from 1990 to 2000. Potential revenue may vary from one year to the next because of both fluctuations in output prices, and changes in potential crop productivity due to local variation weather and climatic conditions. We calculate potential revenue (M3) in every year from 1990 to 2000 as

$$M3_{i,t} = L_{i,2000} \cdot \sum_k p^k_{c,t} \cdot A^k_{i,t} \cdot s^k_{i,2000}.$$

The third variable of interest is maximum potential revenue, $M1_{i,2000}$, which is calculate in 2000.[13] This variable is constructed by holding total agricultural land fixed at its 2000 value, and assuming that farmers both produce maximum attainable yields for every crop and grow the optimal portfolio. In particular, the vector of optimal crop shares is determined as follows:

$$\boldsymbol{s}^*_{i,2000} = \text{Argmax}_{s^k_{i,2000} \in [0,1]} L_{i,2000} \sum_k p^k_{c,2000} \cdot A^k_{i,2000} s^k_{i,2000}.$$

The solution to this problem is full specialization, in which all agricultural land is devoted to the revenue maximizing crop, k^*, and all other crop shares are set equal to zero. The maximum

[12] We discuss the possible reasons for these two variables to differ, and note that differences between actual and potential revenue may still be fully consistent with farm optimization in the following section.

[13] We discuss the construction of the final variable of interest, M2, in the following section.

attainable revenue, $M1_i$, is calculated as

$$M1_{i,2000} = L_{i,2000} \cdot p^{k*}_{c,2000} \cdot A^{k*}_{i,2000}.$$

This variable reflects the maximum revenue that farmers could earn on a particular plot of cultivated land. The gap between $M1_{i,2000}$ and $M3_{i,2000}$ reflects losses attributable to 'crop misallocation': the fact that farmers did not allocate all land to the highest return crop.

3 Results

3.1 Losses in Agricultural Revenue

To begin the analysis, we explore the size of losses in agriculture. Table 2 reports the estimates of actual plot revenue in 2000, potential plot revenue holding cultivated land and crop shares at their 2000 values, and maximum potential revenue holding total cultivated land fixed but allowing producers to reallocate land across crops. All three variables are calculated per hectare of cultivated land and are reported in 2000 USD. We report the results separately for the full sample and for a restricted sample of plots in which the best crop was grown on at least 5 percent of cultivated land.[14]

Panel A reports the estimates of actual and potential revenue per hectare in 2000. The first row reports the maximum potential revenue, given local geographic and climatic conditions. These estimates reflect the revenue that could be earned if farmers maximized agricultural yields and allocated all farmland to the most productive crop. On average, maximum potential revenue was higher in below-median GDP countries (cols. 3-6). These findings are consistent with Adamopoulos and Restuccia (2016), who show that differences in natural endowments cannot account for the agricultural productivity gap in poor countries. These results do not suggest that climatic and geographic conditions played no role in cross-country agricultural out-

[14] This sample restriction limits concerns that mis-measurement of local crop prices could cause us to overstate to the losses attributable to misallocation.

put differences. In particular, farmers in low income countries may have been more vulnerable to volatile output yields caused by climatic and weather shocks, despite having higher *average* potential yields. The second row reports potential revenue per plot, based on observed cultivated land shares in 2000, assuming that farmers achieved maximum crop yields given land and climatic constraints. These estimates reflect the revenue that could be if farmers adopted state-of-the-art production technologies, but did not alter the composition of land fixed. Finally, the third row reports actual revenue per hectare.

Panel B reports the loss estimates, and decomposes them according to source. Overall, rural producers earned roughly 30 percent of potential agricultural revenue. Revenue losses were larger in lower income countries: In above-median GDP countries, actual revenue accounted for 41 to 45 percent of maximum revenue, in below-median GDP countries actual revenue acounted for 21 to 24 percent of maximum revenue. These losses are calculated holding constant natural endowments, and reflect differences in the decision-making of rural producers.

To explore the sources of the production gaps, we decompose revenue losses into two broad categories: i) within-crop production distortions, and ii) cross-crop misallocation. The second row in Panel B reports the ratio of actual revenue (M4) relative potential revenue (M3). The gap between these measures reflects within-crop production distortions due to the fact that given a particular allocation of land, producers did not achieve agronomically feasible returns. In above-median GDP countries, producers achieved returns that ranged from 77 to 83 percent of potential. In below-median GDP countries, returns were 49 to 54 percent of potential returns. In practice, if farmers achieved maximally feasible crop yields, revenue in higher income countries would increase from 41 (45) to 49 (58), and revenue in lower income countries would increase from 22 (24) to 40 (49) percent of maximum potential earnings, leading to a reduction in the revenue gap across countries.

These differences may reflect differences in input technologies. Previous research has identified a number of determinants of these within-crop productivity losses. Various explanations include low intermediate inputs and the misallocation of inputs across farms (e.g. Restuccia, Yang, and Zhu, 2008; Adamopoulos and Restuccia, 2011), the selection of less productive workers into the agricultural sector (e.g. Lagakos and Waugh, 2013), and underinvestment in farm technology due to rural producers' inability to insure against idiosyncratic risks (e.g. Donovan, 2014). It may also be the case that these revenue losses reflect optimal response to cross-country differences in input prices. For example, if farmers in low income countries chose to adopt lower production technologies.[15]

The third row in Panel B reports potential revenue as a percentage of maximum potential revenue under full specialization. These estimates reflect losses due to the fact that land was devoted to crops that did not maximize farm revenue. We estimate that cross-crop distortions were associated large losses in revenue, particularly in lower income countries. These results suggest that understanding the sources of crop-misallocation are critical for the understanding agricultural productivity gap.

Before exploring potential determinants of crop-misallocation, we first provide evidence on the pervasiveness of the different sources of agricultural loss. Figures 3-5 present the distributions of revenue losses separately for above- and below median income countries. Figure 3 reports the distribution of actual revenue relative to maximum potential revenue. Consistent with the statistics reported in Table 2, there were gaps between maximum potential earnings, particularly in lower income countries. In these lower income countries, the distribution was concentrated below 40 percent. Actual returns were substantially higher in above-median countries. In fact, production exceeded maximum potential on 10 percent agricultural land. Figure 4 reports the distribution of within-crop output losses. Again, there are clear differences in the patterns of production by country income, consistent with previous research on differences in input choice by country income (e.g. Donovan, 2016). Figure 5 reports the losses from crop misallocation. These losses were particularly severe in lower income countries, where the mass of the distribution is concentrated around 50 percent. In higher income countries, losses from misallocation were less widespread. On the majority of plots land, misallocation losses were

[15] Our estimates of losses from uncertainty rely on the particular structure of the crop-return covariance matrix, and are independent of local input price differences.

less than 25 percent.

3.2 Determinants of Crop Misallocation

The large losses attributable to cross-crop distortions suggests that, in many areas, land was not allocated to its most productive use. There are two potential explanations for this result. First, crop misallocation may have been caused by farmers having specialized in crops that did not maximize revenue. This situation could reflect differences between local producer prices and national-level crop prices. High transportation costs and poor market access could cause within-country variation in agricultural prices, implying that the optimal crop allocation under national prices may have differed from the optimal allocation under local prices. Differences in input costs across crops could also lead the revenue maximizing allocation to differ from the profit maximizing optimal crop allocation. Government agricultural policies, such as quotas or crop-specific subsidies, could also distort the observed crop allocation away from optimum. Any of these price distortions could lead to crop misallocation and cause farmers should allocate land to crops that do not maximize observed revenue. Because these distortions do not influence the incentive to produce multiple crops, however, this scenario should still be associated with high level of specialization within-plots.

A second possibility is that land was allocated across multiple different crops in ways that did not maximize plot revenue. Differences in production decisions across farms could be the result of information problems which could cause decision-making of some rural producers to differ from optimum. Heterogeneous access to credit could also limit the ability of some farmers to allocate land optimally. It is also possible that highly localized differences in land productivity could lead the optimal local crop allocation to diverge from the average plot-level optimum. Similarly, rural producers may have adopted outdated crop-cycling practices, rotating land between higher and lower productivity crops in an effort to preserve soil nutrients.[16] Finally, the

[16]The agronomic model used by the FAO to construct potential yields accounts for optimal fallow periods and fertilizer usage to best preserve long-run soil quality.

results could reflect an incentive among rural producers to smooth annual income fluctuations. Given the highly volatility of incomes, caused by both output price fluctuations and variable climatic conditions (e.g. Carter, 1997; Shanahan et al., 2009), and the lack of formal insurance mechanisms (Udry et al, 2016), rural producers may optimally diversify cropland in an effort to reduce exposure to negative income shocks.

Table 3 presents information on the allocation of land across crops to shed light on the sources of crop misallocation. Crop diversification was widespread. Nearly five difference crops were grown on the typical plot of land. On average, the main crop accounted for 56 to 58 percent of agricultural land, and full specializiation occurred on just 5 percent of plots. These results are most consistent with the second scenario in which the allocation of land across multiple different crops led to a divergence between observed and revenue maximizing returns, rather than rural producers having specialized in suboptimal crops.

Table 3, cols 3-6 show that crop diversification was particularly widespread in lower income countries. Rural producers grew roughly two additional crops per land, and the main crop accounted for less than 50 percent of agricultural land on the majority of plots. Specialization was more common in higher income countries. Roughly 8 percent of plots were fully specialized, and the main crop accounted for more than 50 percent of agricultural land on three quarter of plots. These results suggest that large agricultural revenue losses in lower income countries can, in part, be explained by the higher levels of diversification. Nevertheless, it remains unclear *why* farmers in lower income countries devoted land to more different crops. In the next section, we assess role of income uncertainty in explaining these patterns.

3.3 Income Uncertainty and Losses in Agriculture

3.3.1 A Model of Crop Diversification

To assess the impact of uncertainty for economic losses in agriculture, we develop a standard mean-variance portfolio problem. This framework has been widely used since Markowitz (1952) to study investor decision-making in the presence of risk. The model, which was originally developed to study the portfolio decisions of investors, applies natural to the decision-making problem of rural producers, who must decide how to allocate land across a variety of crops that have different expected returns and carry different levels of risk. The results provide a benchmark against which we can compare the actual crop choices of farmers.

We consider a rural economy with one unit of agricultural land.[17] Let $\boldsymbol{s}$ be a k-vector where each element s_k denotes the fraction of land devoted to crop k and $\sum_k s_k = 1$. Farmers are assumed to face uncertainty in the realization of individual crop returns, which may be correlated across crops. Let $\boldsymbol{r}$ denote the k-vector of mean crop returns with typical element r_k, and $\boldsymbol{V}$ as a $k \times k$ covariance matrix with typical element σ_{ij} denoting the covariance between the returns for crops i and j.[18] According to this setup, any portfolio of crops chosen by the farmer, $\boldsymbol{s}$, can be characterized by an expected return, R_p, and variance, σ_p^2:

$$R_p = \boldsymbol{s}^T \boldsymbol{r} = \sum_k s_k r_k, \quad \sigma_p^2 = \boldsymbol{s}^T \boldsymbol{V} \boldsymbol{s} = \sum_i \sum_j x_i x_j \sigma_{ij}.$$

The farmer is assumed to trade-off higher returns against increased risk in the portfolio according to the following formulation:

$$\begin{aligned} &\text{maximize} && R_p = \boldsymbol{s}^T \boldsymbol{r} \\ &\text{subject to} && \sigma_p^2 = \boldsymbol{s}^T \boldsymbol{V} \boldsymbol{s}, \quad \boldsymbol{s}^T \mathbf{1} = 1, \quad \boldsymbol{s} \geq \mathbf{0}. \end{aligned} \tag{1}$$

The farmer's problem is to maximize the portfolio return subject to three constraints. First, the variance of the portfolio cannot exceed a desired level, σ_p^2. Second, the amount of land used for agricultural production cannot exceed the total amount available. Third, the amount of land devoted to each crop must be non-negative.[19]

[17] This normalization abstracts from decisions over how much land to devote to agriculture.

[18] To ensure that $\boldsymbol{V}$ is nonsingular and positive definite, we assume that no two crops have perfectly correlated returns and that all crops have strictly positive variances.

[19] This constraint is equivalent to a short-selling restriction in the standard portfolio asset allocation problem.

The solution to the problem is an optimal set of weights, $\boldsymbol{s}^*$, that achieves the highest expected return given an particular level of portfolio volatility.[20] Solving for the optimal weights for different values of σ_p^2, we can trace out the mean-variance efficient (MVE) locus, the portfolio mean-variance pairs (R_p, σ_p^2) that provide the highest return for a given variances.[21] Figure 1 displays the upward-sloping MVE locus. Intuitively, as the tolerance for risk increases, the farmer is able to achieve greater expected returns. All combinations of (R_p, σ_p^2) that fall below this locus are suboptimal, since the farmer could achieve higher expected returns without increasing risk. We denote R_i^{Max} as the highest possible return the farmer could obtain on a plot of land, i. Meanwhile, let denote R_i^G as the return associated with the global minimum variance portfolio – the crop choice with the lowest variability.

This simple framework can be applied to assess the impact of uncertainty on agricultural losses. Figure 2 provides intuition for the analysis. Consider a farmer operating on a plot of land, i, who chooses a vector of crops, $\boldsymbol{s}_i$ that yields a return-variance combination (R_i, σ_i^2). Given the particular characteristics of the plot, R_i^{Max} represents the maximum revenue that could be generated on the plot under full specialization. Meanwhile, R_i^* represents the return from the efficient crop portfolio based on the observed plot variance, σ_i^2. This value reflects the highest agricultural earnings that could be earned without increasing the farmer's level of risk exposure.

Total revenue losses on plot i, $R_i^{Max} - R_i$, can be decomposed into two sources: 1) losses attributable to uncertainty, $R_i^{Max} - R_i^*$, and 2) residual losses from 'crop misallocation', $R_i^* - R_i$. The first term reflects losses caused by the fact that farmers may diversify their crop portfolio to reduce income volatility. This gap reflects that fact that crop diversification lowers expected returns, and given a particular risk tolerance, σ_i^2, it is impossible for farmers to achieve maximum returns. The second term reflects the residual losses from 'crop misallocation' that

[20]The farmer's specific utility function does not enter the problem, although portfolio optimization has been shown to be consistent with expected utility maximization with quadratic utility (see Ingersoll, 1987, for a discussion).

[21]An analytic solution to (1) does not exist, although the optimal weights can be calculated using numerical methods

cannot be attributable to uncertainty. These distortions could be the result of many factors, including differences between local and national output prices, differences in crop-specific input costs, and government policies that distort production across crops.

To apply this framework empirically, we use information on the crop portfolio, $\boldsymbol{s}_i$, and the vector of potential crop returns, $\boldsymbol{r}_i$, for every plot i in the year 2000. We also require information on the level on uncertainty facing farmers. We combine annual changes in crop productivity, $M3_{i,t}$ and output prices, $p^k_{c,t}$, from 1990 to 2000 to construct the plot-specific covariance matrix, $\boldsymbol{V}_i$, with typical element, σ_{jk}, denoting the covariance in returns between crops j and k over the time period. These elements depend both on annual variation in local climatic conditions that differentially impact the potential yields of each crop, and annual co-movements in output prices.[22] Crucially, our analysis is based on variation in exogenous potential crop returns, rather than variation in actual crop returns that may be influenced by the decision-making of rural producers.[23] We combine the covariance matrix, $\boldsymbol{V}_i$, with the observed land allocation in 2000, $\boldsymbol{s}_i$, to calculate variance of potential returns: $\sigma^2_i = \boldsymbol{s}^T_i \boldsymbol{V}_i \boldsymbol{s}_i$. This variable captures the level of risk facing farmers, given their chosen crop portfolio. Given the plot variance, σ^2_i, we solve the farmer's problem in (1) to determine the MVE crop portfolio, $\boldsymbol{s}^*_i$, that provides the highest potential return for the given plot variance, σ^2_i. We combine the MVE crop portfolio with the vector of potential crop returns in 2000 to calculate the maximum potential return given the observed risk tolerance (or MVE potential return): $M2^*_{i,2000} = \boldsymbol{s}^{*T}_i \boldsymbol{r}_i$.

To assess the impact of uncertainty on agricultural losses, we combine information on potential crop revenue, $M3_{i,2000}$, maximum potential revenue, $M1_{i,2000}$, and the MVE potential crop revenue, $M2^*_i$. We decompose the total losses from 'crop misallocation, $\Delta_i = M1_{i,2000}/M3_{i,2000}$, into the fraction that can be explained by economic uncertainty, $\Delta^{\text{Uncertainty}}_i = \left(M1_{i,2000}/M2^*_{i,2000}\right)$, and the residual gap between observed potential returns and maximum potential returns, $\Delta^{\text{Residual}}_i = \left(M2^*_{i,2000}/M3_{i,2000}\right)$. Our identification strategy exploits the spe-

[22]In robustness exercises, we re-estimate the covariance matrix based solely on annual changes in potential yields, holding output prices fixed at their 2000 levels.

[23]For example, farmers might undertake costly investments to mitigate the effects of a rainfall shortage.

cific structure of the covariance in crop returns, that are driven by exogenous climatic and output price fluctuations. As a result, we can decompose the sources of agricultural losses into two broad sources: 1) those that are explained by uncertainty and 2) those driven by farmer decisions that are orthogonal to portfolio risk.

3.3.2 Economic Uncertainty and Losses in Agriculture

To what extent did rural producers face uncertain returns? Table 4 reports estimates of potential revenue volatility for the period 1990 to 2000. The standard deviation in potential returns was 28 to 29 percent of average annual earnings under full specialization. The baseline levels of rural income uncertainty were similar across higher and lower income countries. Nevertheless, farmers responded variable differently to the same underlying risk. Producers poorer countries adopted crop portfolios that were less variable than producers in richer countries. These heterogeneous responses may partly explain the differences in revenue losses across countries (Table 2, panel B), and are consistent with different levels of diversification reported in Table 3.

Motivated by the high level of income uncertainty and the extent to which agricultural land is diversified across multiple crops, we decompose the sources of 'crop misallocation'. Table 5, Panel A reports the estimates of potential revenue per hectare under the current crop allocation, $M3_{i,2000}$, the mean-variance efficient portfolio given the observed plot variance, $M2^*_{i,2000}$, and the revenue maximizing allocation, $M1_{i,2000}$. In panel B, we decompose the losses from crop misallocation, Δ_i, that were driven by uncertainty, $\Delta_{\text{Uncertainty}}$, and other factors, $\Delta_i^{\text{Residual}}$.

Economic uncertainty led to large losses in agricultural revenue. We estimate that 80 percent of 'crop misallocation' losses can be attributed to the gap between the returns under the MVE portfolio and the returns under full specialization. These results suggest that there was little scope for rural producers to have increased plot returns without taking on additional risk. The remaining 20 percent of agricultural losses were due to residual distortions that were uncorrelated with uncertainty motives. These factors reflects other forces driving farmers to divert land from revenue maximizing crops, and might have included differences between local and national level output prices or crop specific input costs, information problems among rural producers, or outdated crop-cycling practices. The effects of income uncertainty were particularly acute in lower income countries. We estimate that the losses from uncertainty were larger in lower income countries ($31 = 100 - 69$ to $37 = 100 - 63$) relative to higher income countries ($30 = 100 - 70$ to $24 = 100 - 76$). Poorer farmers were also more likely to deviate from full specialization for reasons unrelated to uncertainty.

In Table 6, we explore the robustness of the loss estimates. For reference, column (1) reports the baseline estimates. In column (2), we explore the sources of revenue uncertainty, re-estimating the potential revenue assuming that farmers faced fixed prices for the period 1990 to 2000, so that the incentive to diversify can be solely attributable to fluctuations in climatic conditions. Estimated losses from crop misallocation are similar, suggesting that the main results are not sensitive to current versus average output prices. When crop prices are held constant, economic uncertainty is estimated to account for a smaller fraction of total crop misallocation. Comparing the estimates in columns (1) and (2), we calculate that annual output price variability can account for roughly one quarter of the losses from crop misallocation, while the remaining three quarters can be attributed to climatic variability.

In column (3), we report results based on calorie-weighted output.[24] This analysis addresses the concern that in many rural areas that had limited access to national markets, calorie content may provide a more accurate measure of output value. Calorie-weighted misallocation losses are slightly smaller than the estimate losses based on country-level prices, perhaps because many small scale subsistence farmers allocated farmland according to crop consumption value. Nevertheless, the relative importance of income uncertainty is comparable to the estimates found in column (2), in which output prices also did not vary from one year to the next.

In columns (4) to (6) we explore the sensitivity of the main findings to several alternative sample restrictions. In column (4) we restrict the analysis to plots on which known crop

[24]Information on crop calorie content was obtained from the FAO (available at http://faostat3.fao.org)

account for at least 75 percent of cultivated land.[25] This sample restriction does not affect the qualititative findings. In column (5), we restrict the sample to plots on which the highest revenue crop accounted for at least 25 percent of cultivated land. By focusing on plots on which farmers grow a large amount of the highest revenue crop, we limit concerns that mismeasurement in prices might to an overestimate of misallocation losses. In practice this sample restriction leads only to a modest reduction in estimated losses (59.5% in column (4) versus 53.7% in column (1)), suggesting that most of the losses from crop misallocation cannot be attributed to mismeasurement of local prices. The total losses from economic uncertainty are unchanged, although, this sample restriction (by construction) leads to a significant decrease in residual losses. In the final column, we exclude plots for which potatoes or cassava were the revenue maximizing crop, for which energy inputs were substantially lower (Pimentel, 2009). In practice, this restriction has little impact on the main findings.

3.3.3 Determinants of Losses Within and Across Countries

Figures 6 reports the distributions of misallocation losses across agricultural plots in above- and below-median GDP countries. Crop misallocation was pervasive. Fewer than 10 percent of plots were fully specialized in high income countries and the median plot earned just 60 percent of maximum potential revenue. The losses from misallocation were even larger in lower income countries. Just 2.7 percent of land was specialized and three quarters of plots earned less than 60 percent of maximum potential revenue.

Figures 7 and 8 decompose the sources of crop misallocation across plots. Rural producers in lower income countries were disproportionately impacted both by economic uncertainty and residual distortions. In above-median GDP countries, almost half of plots achieved variance efficient returns that were greater than 80 percent of maximum output, and fewer than 20 percent of plots had residual losses that were larger than 20 percent. In contrast, in below-median GDP countries, just 20 percent of plots had M2 returns that exceeded 80 percent, and

[25] In practice, fodder accounts for the majority of unknown cultivated land.

more than 40 percent of plots experienced residual losses that were greater than 20 percent.

The previous results show that crop misallocation was pervasive across much of the world's cultivated land, and that both economic uncertainty and residual distortions contributed to losses on a majority of plots. What remains unclear is the extent to which these losses varied across countries, and the relative importance of economic uncertainty and residual distortions in explaining regional variation in crop misallocation. To examine these questions, we estimate the impact of economic uncertainty and residual distortions on within- and across-country variation in crop misallocation. To separately identify the causal impact of economic uncertainty and residual distortions, we report the results after controlling for any remaining correlation for each explanatory variable.[26]

The top panel of Table 7 decomposes the sources of crop misallocation into variation that occurred within- and across-countries. We find that roughly one-third of the total variation was driven by within-country variation while the remaining two-thirds was driven by cross-country variation. Decomposing the source of this variation, we find that roughly three quarters of within-country variation in crop misallocation can be attributed to differences in economic uncertainty, while the remaining one quarter was the result of unexplained residual local losses. Economic uncertainty was an even greater driver of crop misallocation across countries, and the relative explanatory power is roughly twice as large in the cross-country analysis (see figures 9 and 10 for the residual plots).

3.3.4 Agricultural Losses in Africa: A Border Discontinuity Approach

The previous results show that economic uncertainty was the principal source of the geographic variation in crop misallocation, and that its impact was disproportinately large on losses across countries. There are a number of potential explanations for this result. First, rural producers in different countries may have been exposed to varying levels of underlying uncertainty due to regional climatic shocks causing different levels of diversification across countries. Sec-

[26]By construction, this adjustment guarantees that all coefficient estimates are equal to one, although in practice, controlling for correlation has little impact on the estimated effects.

ond, the results could simply reflect the wide differences in economic conditions across countries that could influence agricultural activity through a variety of channels including credit market access, input costs and technological adoption, and non-agricultural employment opportunities (e.g., Adamopoulos and Restuccia, 2011; Lagakos and Waugh, 2013; Donovan, 2014). A third possibility is that the results capture differences in government policies aimed at reducing uncertainty in the agricultural sector.

We study the sources of agricultural losses in Africa. The African context provides a particularly useful case study on the effects of economic uncertainty for three main reasons. First, local variability in weather conditions are an important source of economic uncertainty (e.g., Bloom and Sachs, 1998; Sachs, 2001), and the vast majority of rural producers lack access to formal insurance and credit markets. Second, modern day country borders were shaped by the historical European colonization, through a process that generally did not consider local ethnic or geographic features (Michalopoulos and Papaioannou, 2017). As a result of the historical partition, farmers facing similar geographic and climatic conditions were exposed to widely different instutional environments. We focus on differences in the evolution of institutions across former English and French colonies. Researchers have argued that the English common law system supports market outcomes, including property rights enforcement, functioning credit markets, and openness to trade (La Porta et al., 2008), all of which may have fostered agricultural development and led to private solutions to rural economic uncertainty. On the other hand, former French colonies typically had larger public sectors and devoted a disproportionate share of public expenditure to the agricultural sector, which may have mitigated the impacts of economic uncertainty.

We adopt a border regression discontinuity approach to study the determinants of crop misallocation in Africa. We estimate the following specification:

$$y_{ibc} = \alpha + \beta British_c + f(dist_{ic}) + \gamma_b + \epsilon_{ibc}, \tag{2}$$

where y_{ibc} denotes agricultural outcome on plot i, located within 100 kilometers of border b, in country c. The model includes a cubic control for plot distance to the border that we allow to vary according to French versus British colonial origin, $f(dist_{ic})$, and a border-specific fixed effect, γ_b. The explanatory variable of interest, $British_c$, is a dummy variable equal to one for former British colonies.[27] The coefficient β captures the combined impact of institutional and economic changes that occurred in countries established under British colonization relative to those that were established under French colonization. The analysis is based on a sample of 8,623 plots of land spanning 14 countries and 10 border pairs. We report double-clustered standard errors at the country and at the border level using the method of Cameron, Gelbach, and Miller (2011) to account for spatial correlation and arbitrary residual correlation within each dimension.

Before reporting the results, we first evaluate the validity of the research design. Table 8 reports the estimated effects of British colonization on potential crop productivity. Intuitively, if country border were created for reasons unrelated to local land characteristics, we should not observe systematic differences in land productivity across former British or French colonies. We report the estimates for five staple crops: maize, pulses, cassava, palm oil, and sugarcane. Panel A reports the coefficient estimates based on all border plots. There is no evidence that agricultural productivity changed discontinously at the country border. The coefficient estimates are all statistically insignificant and generally small in magnitude. These results broadly support the identifying assumptions that the drawing of country borders under colonization was largely made independently of considerations of localized geographic conditions. Panel B reports the results for plots that had positive cultivated land. Again there are no significant differences in crop productivity across countries, suggesting that different policies that developed following British colonization had little effect on extensive margin decisions over which land was cultivated.

Table 9 reports the results for agricultural output. Columns (1) to (3) report the overall

[27] To avoid misassignment of the relevant country to agricultural land, we exclude plots located within 10 kilometers from a border.

impact of the British system on revenue losses in agriculture (M4/M1). Observed agricultural returns were somewhat higher in former British colonies, although none of the differences are statistically significant. We decompose the sources of these revenue differences into crop misallocation (cols. 4-6) and within-crop distortions (cols. 7-9). The results show that the small overall impacts were the result of two offsetting forces. Farmers in former British colonies appear to have adopted more advanced inputs, achieving higher crop-specific returns. At the same time, producers in former British colonies displayed higher levels of crop misallocation. Together these results show that despite having limited overall impact on overall agricultural output, the economic and institutional systems that developed following British and French colonization differentially affected the decision-making of rural producers.

Table 10 decomposes the sources of crop misallocation across former British and French colonies. Roughly two thirds of the gap in crop misallocation can be explained by economic uncertainty (cols. 7-9). In particular, despite having access to equally productive land and facing similar climatic conditions, farmers in former French and British colonies responded differently to output risk. Producers in former French colonies took on greater levels of risk, and adopted a less diversified and higher yield crop portfolio. Consistent with this result, we estimate significant cross-country differences in the number of crops grown, with farmers in former British colonies growing an additional 1.3 crops per plot on average. The remaining one third of the gap can be accounted for by residual factors that disproportionately affected the allocation of land in former British colonies (cols. 4-6).

The results in Tables 9 and 10 show that farmers in former British colonies achieved higher crop-specific yields, but adopted a more heavily diversified crop portfolio. These findings reflect the combined effects of the many differences in legal and institutional arrangements that emerged post-colonization. The British common law system is thought to have fostered growth and political stability by promoting a host of private sector reforms. Consistent with this view, former British colonies had higher levels of GDP per capita, had a higher levels of trade. Former British colonies also score higher on the polity IV index of democratization. Meanwhile, former

French colonies had higher levels of government expenditure as fraction of GDP and devoted a disproportionate share of government spending to the agricultural sector. These different institutional arrangements and economic conditions appear to have impacted the decision-making of rural producers. On the one hand, farmers in former British colonies adopted more intensive agricultural techniques, and achieved higher crop-specific returns. This gap might have been driven by the private sector expansion and improved credit markets that fostered investments in agricultural inputs. On the other hand, these same farmers were more heavily influenced by economic uncertainty, perhaps because they lacked access to the security provided the government.[28]

4 Conclusion

Using FAO data on agriculture for cultivated areas that spans all arable land, this paper estimates the revenue losses in agriculture. We identify a new source of misallocation associated with the fact that agricultural land is often not allocated to the highest revenue crops. 'Crop misallocation' was an important driver of losses in agriculture, and revenue could be increased by almost 100 percent if currently cultivated land were allocated to its most productive use. Applying a standard portfolio theory framework to historical data on annual potential crop yields and agricultural prices, we find that uncertainty over annual income was the primary reason why farmers did not specialize. The losses attributable to income uncertainty were particularly large in lower income countries. Nevertheless, comparing agricultural outcomes across the borders of African countries, we find that pro-private sector policies in former British colonies led to greater investment in agricultural inputs, but did not mitigate the effects of economic uncertainty. Instead, it appear that a combination of well-functioning private systems along with non-market public interventions that reduce exposure to risk are needed to foster

[28] In fact, under the Comprehensive Africa Agriculture Development Programme (CAADP), a target was set for African countries to allocate at least 10 percent of public expenditures to the agricultural sector. One of the four pillars of this progam was "reducing the vulnerability of rural households and risk management".

broad-based improvements in agricultural outcomes in developing countries.

This paper's findings have relevance for policies aimed at rural economic development. Much of the recent empirical literature has emphasized the importance of major infrastructure investments (e.g Adamopoulos, 2011; Tombe, 2014; Dinkelman, 2011) and rural production technologies (e.g. Donovan, 2014). Nevertheless, these projects require major upfront investments and the benefits may only emerge after a period of several decades (Devine Jr, 1983; David, 1990; Lewis and Severnini, 2017). This paper's results suggest that policies aimed at risk reduction may also promote rural economic development.

It is important to emphasize that our estimates likely do not reflect the full effects of agricultural income uncertainty. In particular, rural residents may have engaged in a variety of alternative strategies to mitigate local risks. These might have included precautionary savings (Deaton 1990; 1991), underinvestment in agricultural technologies (Donovan, 2014), or cross-regional insurance. A comprehensive assessment of the economic costs of rural income uncertainty must also account for the losses stemming from these other mitigation strategies.

Finally, it is important to emphasize that our partial equilibrium estimates are unlikely to reflect the general equilibrium impacts of broad-based programs aimed at lowering rural income uncertainty, which will ultimately depend on output price elasticities. Nevertheless, there may still be wide scope for risk-mitigation policies to improve welfare, by lowering the labor demands needed to meet subsistence consumption requirements, and promoting the rural-transition. Further study of the general equlibrium consequences of these policies is a potentially interesting avenue for future research.

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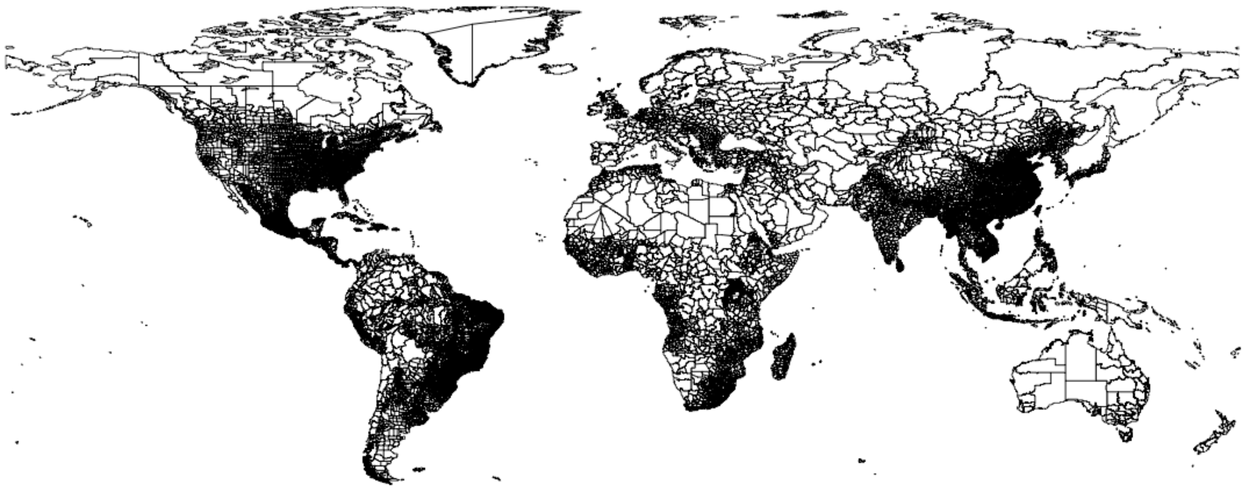
Figure 1: Political Units for Crop Production



Notes: This map shows the political units used in the crop data set. These include 2299 political units one level below the country (e.g., state or province) from 150 countries, and 19,751 units two levels below the country (e.g., county or district) for 73 countries. Source: Monfreda, Ramankutty, and Foley (2008).

Figure 2: Mean-Variance Efficient Portfolios

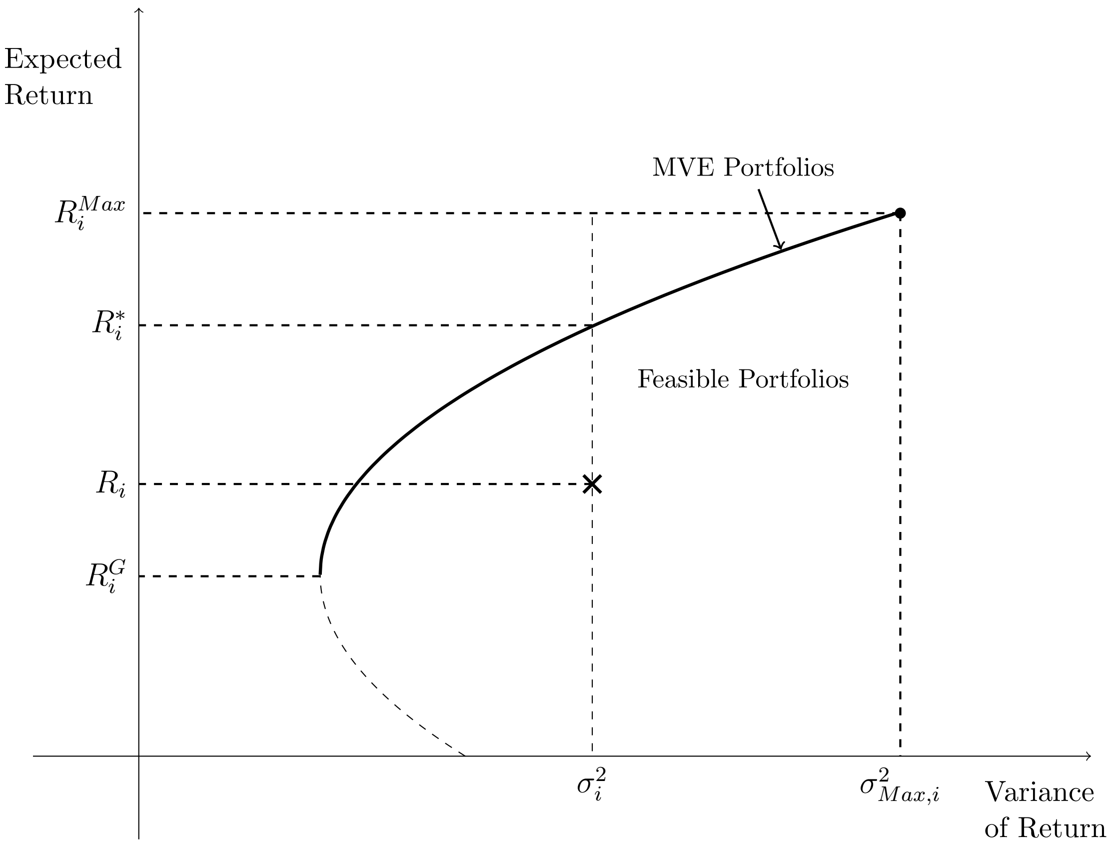
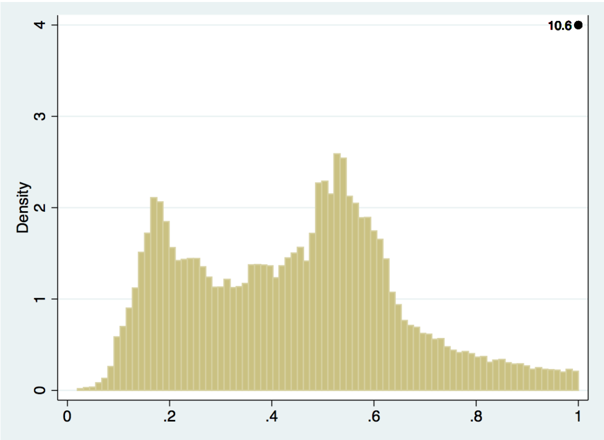
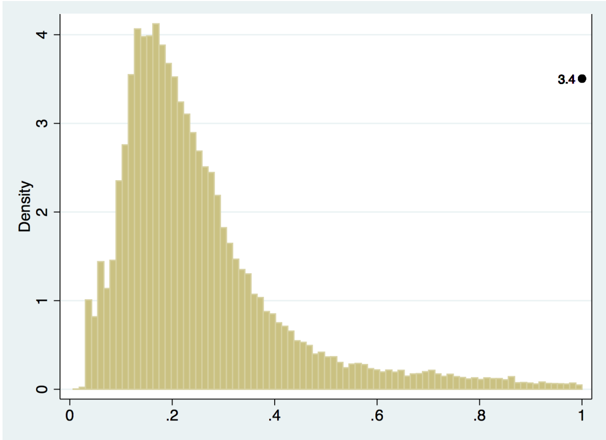


Figure 3: Total Losses in Agriculture: M4/M1

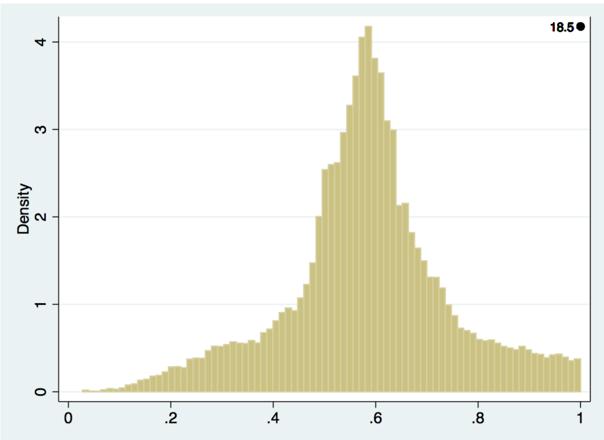


(a) Above median GDP

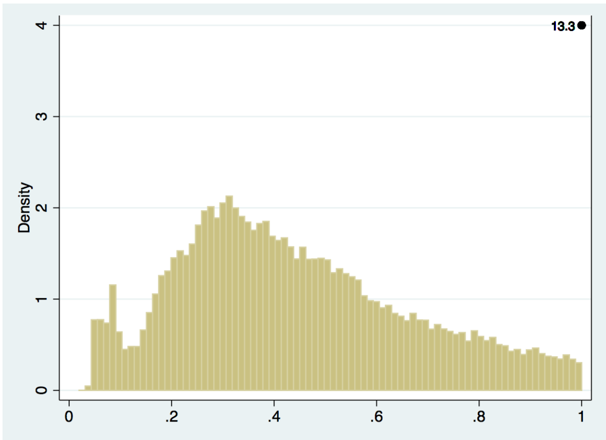


(b) Below median GDP

Figure 4: Losses from Productivity: M4/M3

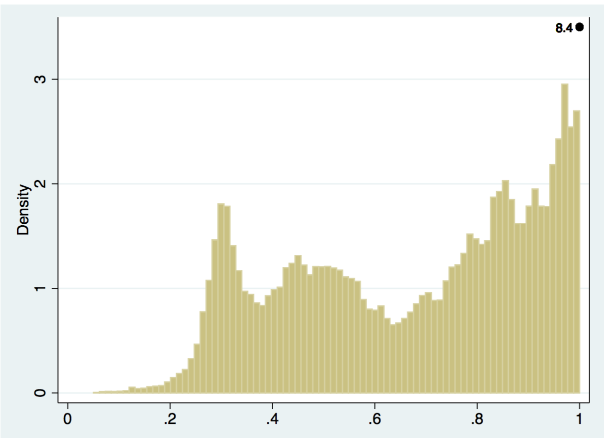


(a) Above median GDP

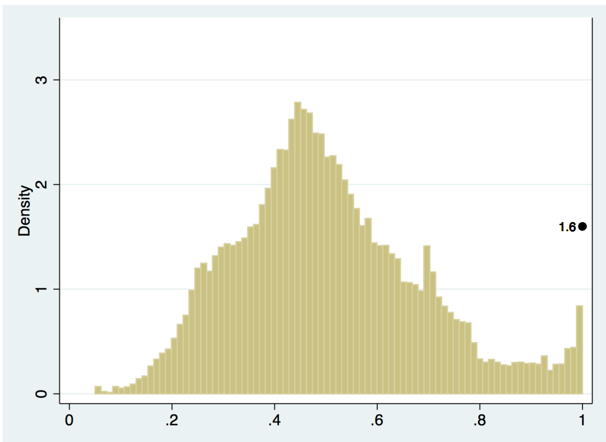


(b) Below median GDP

Figure 5: Losses from Misallocation: M3/M1

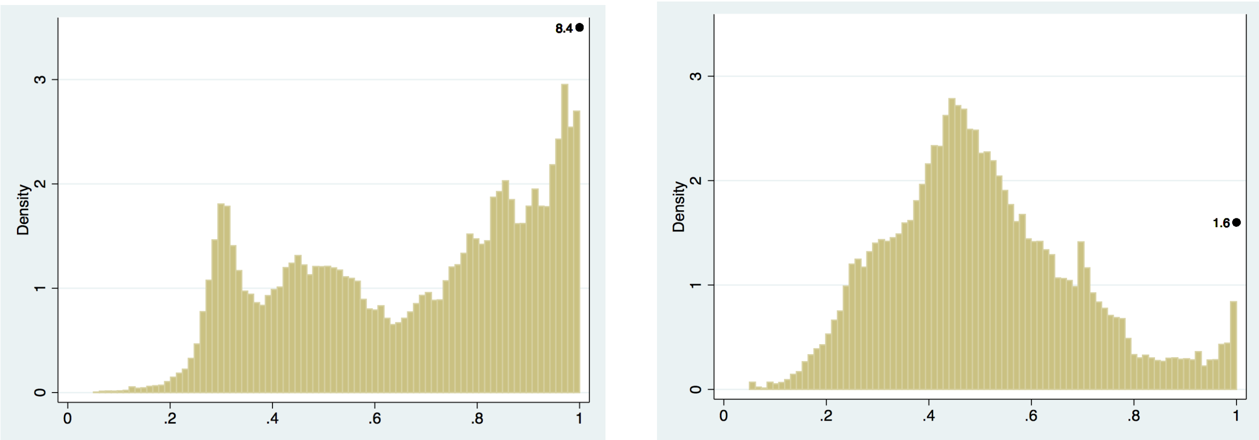


(a) Above median GDP



(b) Below median GDP

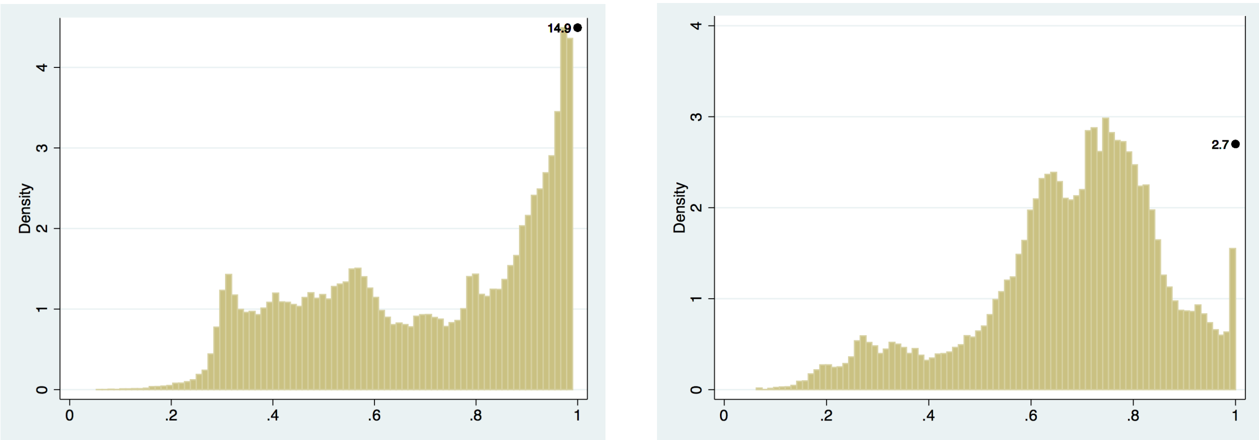
Figure 6: Misallocation in Agriculture: M3/M1



(a) Above median GDP

(b) Below median GDP

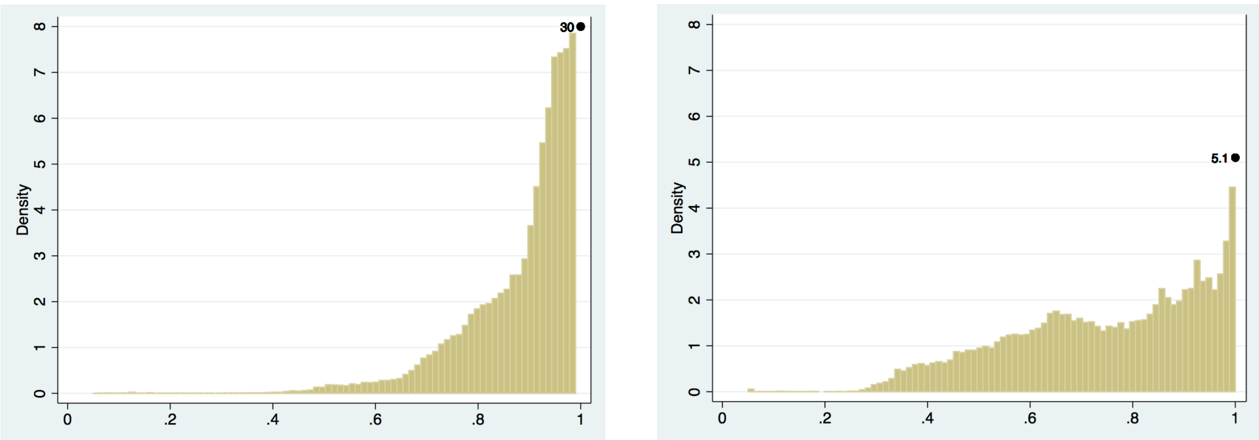
Figure 7: Losses from Insurance



(a) Above median GDP

(b) Below median GDP

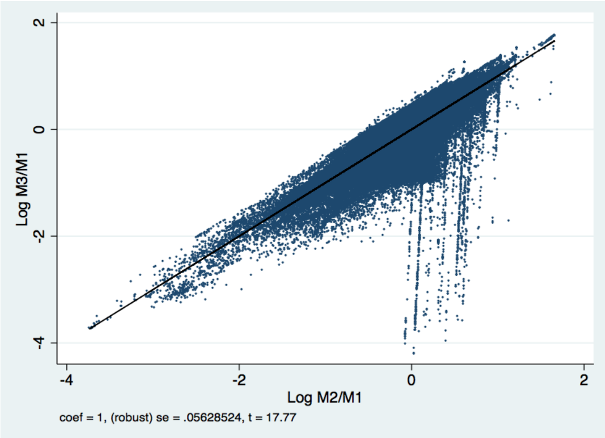
Figure 8: Residual Losses



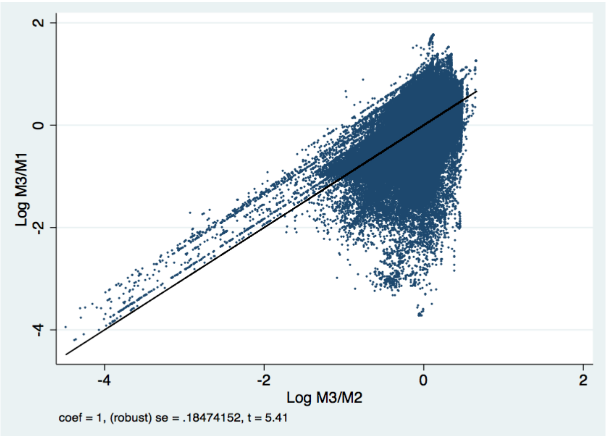
(a) Above median GDP

(b) Below median GDP

Figure 9: Determinants of Misallocation (Log M3/M1): Within Countries



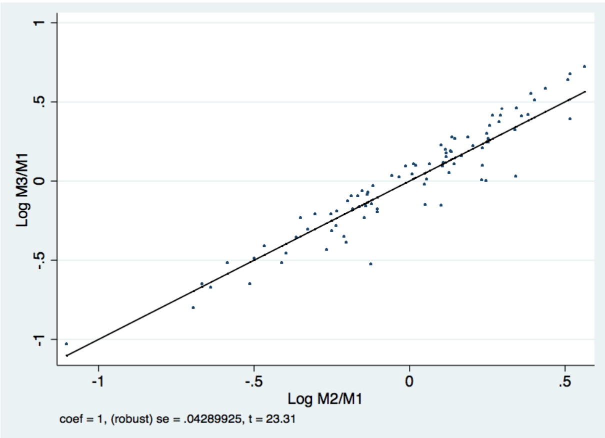
(a) Economic Uncertainty



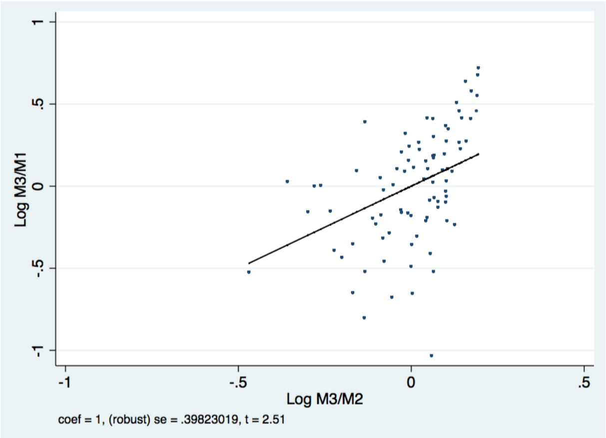
(b) Residual

Notes: These figures report the residual plots on the determinants of Log M3/M1 within countries that correspond to Table 7, col. 1.

Figure 10: Determinants of Misallocation (M3/M1): Across Countries



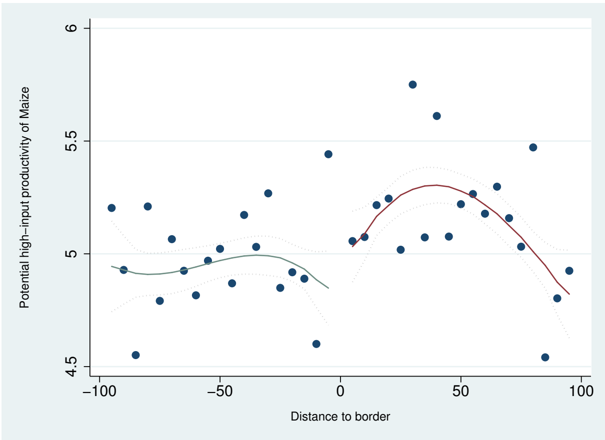
(a) Economic Uncertainty



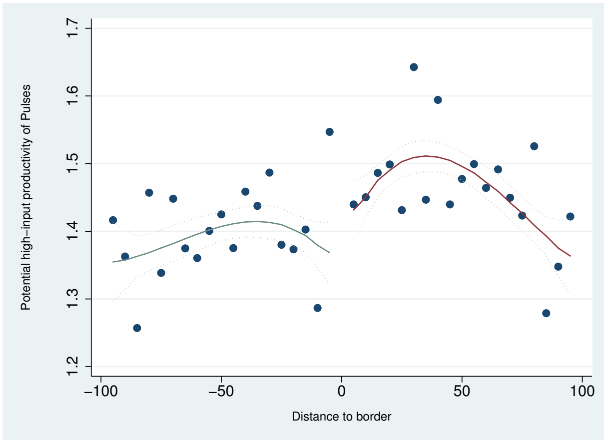
(b) Residual

Notes: These figures report the residual plots on the determinants of Log M3/M1 across countries that correspond to Table 7, col. 4.

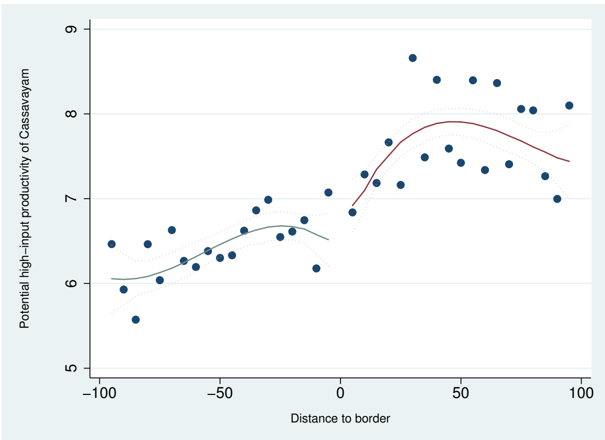
Figure 11: Potential Productivity by British verus French Colonial Origin



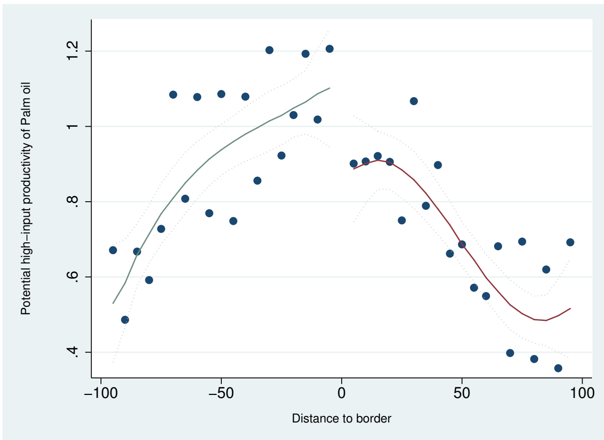
(a) Maize



(b) Pulses



(c) Cassava



(d) Palm Oil

Notes: These figures report potential productivity for each crop across former British (left-hand side) and French (right-hand side) colonies, by average plot distance to the border.

Table 1: Agricultural Land, by Crop and by Country

Panel A: Agricultural land, by crop

Crop	Cultivated Land (Millions Ha)	% World Arable Land	% Cropland in sample	% Land Allocated to Crop: Below median GDP	% Land Allocated to Crop: Above median GDP
All	899	64.2	63.7		
Wheat	215	15.4	57.9	13.1	28.7
Rice	154	11.0	39.3	24.7	4.6
Maize	138	9.9	73.1	8.8	21.5
Soybean	74	5.3	77.1	3.3	19.5
Pulses	45	3.2	103.4	12.0	4.6
Sorghum	41	2.9	57.1	8.3	2.4
Millet	37	2.7	43.6	10.6	0.1
Potato	30	2.1	59.7	1.0	1.2
Cassava, Yam	25	1.8	101.6	4.2	1.3
Cocoa, Coffee, Tea	25	1.8	106.9	3.5	2.8
Rapeseed	26	1.8	73.9	2.0	3.5
Groundnut	23	1.7	53.6	4.8	0.4
Sunflower	21	1.5	45.0	0.5	2.5
Sugarcane	19	1.4	78.9	2.0	2.5
Oilpalm	10	0.7	63.3	0.9	1.5
Olive	8	0.6	54.4	0.2	2.0
Sugarbeet	6	0.4	84.6	0.0	0.9

Panel B: Agricultural land, by Country

	% Country's Arable Land		% Country's Arable Land		% Country's Arable Land
World	60.8	Germany	43.0	Niger	58.2
Algeria	19.1	Ghana	113.1	Nigeria	83.0
Argentina	82.3	Greece	68.6	Pakistan	15.1
Australia	24.5	Guinea	72.2	Panama	42.6
Austria	47.4	Honduras	80.9	Paraguay	73.0
Bangladesh	143.3	Hungary	61.4	Peru	21.4
Belize	83.4	India	87.9	Philippines	145.2
Bhutan	88.0	Indonesia	105.3	Poland	33.8
Bolivia	53.9	Iran	40.8	Portugal	56.8
Botswana	16.0	Ireland	10.1	Rwanda	72.6
Brazil	73.3	Israel	39.0	Senegal	55.8
Brunei	36.6	Italy	64.1	South Africa	23.0
Burkina Faso	86.6	Jamaica	43.1	Spain	29.7
Burundi	64.7	Japan	44.9	Sri Lanka	119.3
Cambodia	56.6	Jordan	37.8	Sudan	13.4
Cameroon	38.5	Kenya	72.4	Suriname	84.1
Canada	42.3	Laos	95.0	Sweden	0.7
Chile	31.5	Lebanon	91.7	Switzerland	38.6
Colombia	113.7	Madagascar	74.6	Tanzania	74.9
Congo	34.8	Malaysia	394.7	Thailand	86.6
Costa Rica	125.9	Mali	55.7	Togo	46.3
Cotedivoire	173.9	Malta	51.4	Tunisia	66.5
Cyprus	15.8	Mexico	53.0	Turkey	54.3
Denmark	34.4	Morocco	31.8	United Kingdom	48.5
Dominican Republic	68.0	Mozambique	64.9	Uruguay	29.1
Ecuador	106.8	Namibia	29.0	United States	46.7
El Salvador	104.4	Nepal	144.1	Venezuela	50.2
Equatorial Guinea	42.2	Netherlands	47.2	Vietnam	158.3
France	54.0	New Zealand	6.6		
Gambia	86.5	Nicaragua	40.1		

Table 2: Actual and Potential Plot Revenue

	All countries		Above median GDP per capita		Below median GDP per capita	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Potential and Actual Revenue per Ha in USD						
Max Potential Rev (M1)	2175.4	1831.4	1877.4	1615.7	2451.8	2018.9
Potential Rev (M3)	953.1	967.5	915.6	935.8	987.8	995.0
Actual Rev (M4)	642.3	596.8	761.8	718.3	531.4	491.1
Panel B: Losses in Revenue						
Actual Rev/Max Potential Rev (M4/M1 %)	29.5	32.6	40.6	44.5	21.7	24.3
Actual Rev/Potential Rev (M4/M3 %)	67.4	61.7	83.2	76.8	53.8	49.4
Potential Rev/Max Potential Rev (M3/M1 %)	43.8	52.8	48.8	57.9	40.3	49.3
Full sample	Y		Y		Y	
Restricted sample: (Best crop $\geq$ 5% cultivated area)		Y		Y		Y

Table 3: Allocation of Cultivated Land

	All countries		Above median GDP per capita		Below median GDP per capita	
	(1)	(2)	(3)	(4)	(5)	(6)
N(crops)	4.8	4.7	3.9	3.7	5.6	5.6
% Land devoted to main crop						
Average	58.0	55.5	62.7	62.0	53.6	49.8
I(>95%)	5.3	5.2	7.6	9.1	2.9	2.1
I(66-95%)	19.9	25.6	27.8	24.3	23.5	16.0
I(50-66%)	31.1	30.9	38.7	38.9	23.6	24.3
I(33-50%)	33.1	29.2	24.5	26.3	33.6	39.0
I(<33%)	10.6	9.2	1.3	1.5	16.5	18.6
Full sample	Y		Y		Y	
Restricted sample: (Best crop $\geq$ 5% cultivated area)		Y		Y		Y

Table 4: Variability in Agricultural Revenue

	All countries		Above median GDP per capita		Below median GDP per capita	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Variability in Plot Revenue						
Standard deviation						
Highest yield crop	761.8	625.0	538.0	457.5	969.3	770.7
Currently cultivated crops	310.7	320.0	214.3	219.4	400.1	407.3
Coeff. of variation (%)						
Highest yield crop	29.1	28.4	28.2	28.4	30.0	28.5
Currently cultivated crops	13.9	15.5	15.0	17.2	12.8	14.0
Full sample	Y		Y		Y	
Restricted sample: (Best crop $\geq$ 5% cultivated area)		Y		Y		Y

Table 5: Uncertainty and Losses in Agricultural Revenue

	All countries		Above median GDP per capita		Below median GDP per capita	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Potential Revenue Estimates						
Max Potential Rev (M1)	2175.4	1831.0	1877.4	1615.7	2451.8	2018.9
MVE Potential Rev (M2)	1180.2	1172.8	1092.1	1055.2	1262.0	1275.0
Potential Rev (M3)	953.1	967.5	915.6	935.8	987.8	995.0
Panel B: Decomposing Revenue Losses						
M3/M1	53.7	59.3	61.1	69.0	46.9	50.9
M3/M2	81.4	82.5	86.9	90.8	76.2	75.2
M2/M1	66.1	71.8	69.8	75.5	62.8	68.5
Full sample	Y		Y		Y	
Restricted sample: (Best crop $\geq$ 5% cultivated area)		Y		Y		Y

Table 6: Uncertainty and Losses in Agricultural Revenue

	Baseline estimates	Fixed prices	Calorie weighted output	Restricted samples: Known crops >75% of cultivated land	Restricted samples: Best crop >25% of cultivated land	Restricted samples: Exclude plots with potato, pulses best crop
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Potential Revenue Estimates						
Max Potential Rev (M1)	2175.4	2061.9	2987.5	1849	1541.6	1888.1
MVE Potential Rev (M2)	1180.2	1395.5	2031.6	1100.4	1228.6	1097.4
Potential Rev (M3)	953.1	958.3	1545.4	945.2	1120.6	885.5
Panel B: Decomposing Revenue Losses						
M3/M1	53.7	54.7	59.3	59.5	78.7	55.4
M3/M2	81.4	74.7	76.4	85.9	92.1	81.4
M2/M1	66.1	74.9	79	59.5	85.0	68.2

Table 7: Determinants of Misallocation

	Within countries			Across countries		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Log Crop Misallocation (Log M3/M1)						
Fraction Variation (dep. var.)	0.33	0.49	0.34	0.67	0.51	0.64
Log(M2/M1)						
R-squared	0.765	0.734	0.725	0.908	0.814	0.943
T-statistic	17.8	20.5	16.7	23.3	14.1	31.9
Coeff	1	1	1	1	1	1
SE	[0.0563]	[0.04879]	[0.05982]	[0.04290]	[0.0708]	[0.0313]
Log(M3/M2)						
R-squared	0.2503	0.3662	0.1781	0.1242	0.1357	0.1348
T-statistic	5.4	6.0	5.4	2.5	3.3	2.2
Coeff	1	1	1	1	1	1
SE	[0.1847]	[0.1662]	[0.1858]	[0.3982]	[0.2988]	[0.4506]
Relative explanatory power: M3/M1 vs. M3/M2						
R-squared Ratio	3.1	2.0	4.1	7.3	6.0	7.0
T-statistic Ratio	3.3	3.4	3.1	9.3	4.2	14.4
Observations	486,872	351,407	450,399	87	87	85
Full Sample	Y			Y		
Best crop $\geq 5\%$		Y			Y	
Trimmed sample			Y			Y

Notes: This table reports the results for the impact of uncertainty (Log M2/M1) and residual factors (Log M3/M2) on crop misallocation (Log M3/M1). Each cell reports the results from a difference regression. All models are weighted by total cultivated area. Standard errors are clustered at the country level.

Table 8: **Legal origin - Effect on revenue outcomes**

	Log Potential Productivity									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Former British Colony	-0.032	-0.152	-0.038	-0.171	0.002	0.099	0.147	-0.187	0.122	0.081
	(0.082)	(0.154)	(0.075)	(0.160)	(0.109)	(0.156)	(0.264)	(0.323)	(0.120)	(0.149)
# Observations	26222	13917	26092	13903	18229	10042	2381	1596	12172	7256
R2	0.308	0.285	0.343	0.376	0.262	0.378	0.460	0.468	0.196	0.338
Crop	Maize	Maize	Pulses	Pulses	Cassava	Cassava	Palm oil	Palm oil	Sugarcane	Sugarcane
Sample	All plots	Cultivated	All plots	Cultivated	All plots	Cultivated	All plots	Cultivated	All plots	Cultivated
Weight	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

NOTES. This table reports, for a given crop indicated at the bottom of the column, RDD estimations of the impact of the legal origin of a country on the potential productivity on any plot. The sample consists of observation within 100 km of a border between two countries who were under different colonial powers. When the bottom row indicates Cultivated, the sample is restricted to observations where some known crop is grown. All estimations include cubic polynomials on either side of the border. Standard errors are clustered at the border level.

Table 9: **Legal origin - Effect on revenue outcomes**

	Log M4/M1			Log M3/M1			Log M4/M3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Former British Colony	0.012	0.507	0.592	-0.252**	-0.404**	-0.484**	0.264	0.911**	1.076**
	(0.333)	(0.374)	(0.378)	(0.100)	(0.164)	(0.155)	(0.319)	(0.363)	(0.390)
# Observations	8652	8652	6492	8652	8652	6492	8652	8652	6492
R2	0.261	0.414	0.401	0.132	0.218	0.178	0.286	0.539	0.526
Weighted	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Without 25% least productive land	No	No	Yes	No	No	Yes	No	No	Yes

NOTES. This table reports RDD estimations of the impact of the legal origin of a country on Log of M4/M1, M3/M1 and M4/M3. The sample of observations consists of all plots where some known crop is grown, within 100 km of a border between two countries who were under different colonial powers. All estimations include border fixed effects. They also include cubic polynomials specific to either side of a border. Standard errors are doubly clustered, at the country and at the border level.

Table 10: **Legal origin - Effect on revenue outcomes**

	Log M3/M1			Log M3/M2			Log M2/M1		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Former British Colony	-0.252**	-0.404**	-0.484**	-0.022	-0.148*	-0.189*	-0.230	-0.256	-0.295*
	(0.100)	(0.164)	(0.155)	(0.062)	(0.079)	(0.091)	(0.135)	(0.181)	(0.158)
# Observations	8652	8652	6492	8652	8652	6492	8652	8652	6492
R2	0.132	0.218	0.178	0.163	0.343	0.354	0.179	0.184	0.145
Weighted	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Without 25% least productive land	No	No	Yes	No	No	Yes	No	No	Yes

NOTES. This table reports RDD estimations of the impact of the legal origin of a country on Log of M3/M1, M3/M2 and M2/M3. The sample of observations consists of all plots where some known crop is grown, within 100 km of a border between two countries who were under different colonial powers. All estimations include border fixed effects. They also include cubic polynomials specific to either side of a border. Standard errors are doubly clustered, at the country and at the border level.