The impact of income, land, and wealth inequality on agricultural expansion in Latin America

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Edited by Anthony J. Bebbington, Clark University, Worcester, MA, and approved December 17, 2018 (received for review August 29, 2018)

Agricultural expansion remains the most prominent proximate cause of tropical deforestation in Latin America, a region characterized by deforestation rates substantially above the world average and extremely high inequality. This paper deploys several multivariate statistical models to test whether different aspects of inequality, within a context of increasing agricultural productivity, promote agricultural expansion (Jevons paradox) or contraction (land-sparing) in 10 Latin American countries over 1990–2010. Here I show the existence of distinct patterns between the instantaneous and the overall (i.e., accounting for temporal lags) effect of increasing agricultural productivity, conditional on the degree of income, land, and wealth inequality. In a context of perfect equality, the instantaneous effect of increases in agricultural productivity is to promote agricultural expansion (Jevons paradox). When temporal lags are accounted for, agricultural productivity appears to be mainly land-sparing. Increases in the level of inequality, in all its forms, promote agricultural expansion, thus eroding the land-sparing effects of increasing productivity. The results also suggest that the instantaneous impact of inequality is larger than the overall effect (accounting for temporal lags) and that the effects of income inequality are stronger than those of land and wealth inequality, respectively. Reaping the benefits of increasing agricultural productivity, and achieving sustainable agricultural intensification in Latin America, requires policy interventions that specifically address inequality.

tropical deforestation | Latin America | agricultural expansion | Jevons paradox | inequality

Tropical deforestation remains an important contributor to climate change and to the loss of biodiversity and of a number of local and global ecosystem functions (1, 2). At the global level, deforestation rates have passed from 0.20% per annum (p.a.) over 1990–2000 to 0.13 p.a. over 2000–2010. Central and South America account for over 20% of the remaining world forests, while experiencing annual deforestation rates well above the world averages (3).

The underlying causes of deforestation, particularly in frontier regions like Latin America, reflect changes in the technological and socioeconomic structure (4, 5). With respect to socioeconomic factors, for example, crop prices, per-capita GDP, commodities exports, and level of external debt appear to be positively correlated with deforestation (4–9). The proximate causes of deforestation, on the other hand, mainly relate to the process of agricultural expansion to supply both internal markets and international commodity markets, followed by timber extraction (10, 11). Understanding what drives agricultural expansion is therefore important to comprehend the problem of deforestation.

A significant aspect in the study of environmental degradation in general, including the analysis of agricultural expansion and deforestation in Latin America, relates to the effect of power and economic inequality. Besides being a hot spot for tropical deforestation, Latin America (together with Sub-Saharan Africa) remains one of the most unequal places in the world (12). The effects of inequality on environmental degradation are still debated. On one hand, a number of theoretical arguments have been put forward for the existence of a positive relationship between inequality and environmental degradation. First, inequality increases the marginal benefits of polluters, while reducing the marginal costs to the victims (i.e., the poor sell cheap) (13–15). As a result the socially optimal level of environmental degradation is likely to be higher in more unequal societies. For example, larger income inequality has been associated to biodiversity loss (16, 17). Larger inequality in income and land distribution has been associated to higher deforestation rates in 48 developing countries (18). Second, greater inequality may hinder the collective action necessary to prevent environmental degradation while at the same time promoting consumerism (19, 20). However, institutional arrangements may temper the impact of rising inequality. For example, forest degradation across various user groups in India, Nepal, Kenya, Uganda, Bolivia, and Mexico is positively correlated to wealth inequality but conditional on the quality of existing institutions (21). Third, when a concave relationship between income and environmental degradation exists at the micro level (i.e., household level), then increasing inequality at the macro level (i.e., aggregated across households) is associated with an increase in environmental degradation (22). On the other hand, there are also theoretical arguments pointing to a negative relationship between inequality and environmental degradation. The existence of powerful elites can facilitate collective action and therefore be beneficial to the environment, particularly when the elite can benefit from the provision of a public environmental good (23, 24). Such a mechanism could explain the fact that higher inequality in land distribution has been associated to lower deforestation across 318 ejidos in Mexico (25, 26). Similarly, high degrees of income

Significance

Over the past few years, there has been a renewed interest on inequality. At the global level, there has been an increase in the concentration of income and wealth with a number of economic, social, and environmental consequences. In this article, I study the relationship between different forms of inequality (namely, income, wealth, and land concentration), agricultural intensification, and agricultural expansion in Latin America. This region represents one of the most active agricultural frontiers in the world while at the same time registering one of the highest rates of inequality. Understanding the role of inequality in directing the process of agricultural intensification toward land-sparing or further agricultural expansion, and consequent deforestation, is important to inform appropriate corrective policies.

Author contributions: M.G.C. designed research, performed research, analyzed data, and wrote the paper.

The author declares no conflict of interest.

This article is a PNAS Direct Submission.

Data deposition: Data related to this work have been deposited at https://datadryad.org (doi:10.5061/dryad.0sn4046).

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1814894116/-/DCSupplemental.

Published online January 24, 2019.

inequality resulted in more land being designated as protected areas in countries where democratic institutions are poor (27). Although protected areas may be unpopular at the local level, they tend to be supported by elites. Where democratic institutions are weak, politicians establishing protected areas do not have to fear for reelection. To sum up, both the theory and the empirical evidence leave the environment–inequality debate still open.

Within this discourse, additional considerations are needed, when looking specifically at the issue of inequality in land distribution in conjunction with demographic pressures. In general, it has been hypothesized that increasing rural population densities could be conducive to agricultural expansion, as suggested by Malthus. Evidence from Central America (28) supports such a hypothesis, but the same is not true for South America, where agricultural expansion has occurred despite declines in rural population densities (29). The availability of land and its concentration is likely to play a crucial role in this respect. For example, the analysis of agricultural land clearance across 59 developing countries shows that inequality in land distribution exacerbates the effect of population density increases on the demand of agricultural area (30). Where land is extremely concentrated, outmigration to the frontier or to other countries is an option. Both factors can in turn lead to further agricultural expansion and consequent deforestation. For example, in frontier regions of the Ecuadorian Amazon, where immigration has fueled population growth, higher population densities are associated to larger forest loss (31). In Central America, remittances from migrants have been invested mainly in expanding agricultural landholdings (32). In South America, where high mechanization and low labor intensity result in large agricultural holdings and low rural population densities, international commodity demand plays an important role in driving agricultural expansion (33, 34).

The purpose of this paper is to contribute to the existing debate, by clarifying how different aspects of inequality may affect agricultural expansion in Latin America. The paper will focus on income, land, and wealth inequality. The inclusion of wealth and land inequality measures in the analysis (despite such data being more sparse) is due to the fact that wealth and land are more concentrated than income (35, 36) and, according to scholars, represent a more durable form of inequality (21). Land inequality in particular is thought to play an important role in the process of agricultural expansion and deforestation (30, 37–39). The novelty of the present study is its focus on the interactions between the inequality measures and agricultural productivity. This interaction is relevant to the land-sparing versus Jevons paradox question. Advocates of the land-sparing hypothesis maintain that agricultural intensification will allow sparing land for nature (40), whereas advocates of the Jevons paradox suggest that intensification will stimulate further agricultural expansion and deforestation (34, 41, 42). The empirical evidence is ambiguous and points to the importance of the institutional setting in promoting land-sparing or Jevons paradox (43). It has already been shown that various forms of inequality can have a significant impact on both political and economic institutions (44–46). A central assumption in this paper is that agricultural intensification, here intended as an increase in agricultural output per unit of land, can have a different impact on the extension of agricultural area, depending on the prevailing institutional context. Different forms of inequality may act on the institutional context and direct the process of agricultural intensification (i.e., increases in agricultural productivity) toward land-sparing or Jevons paradox.

Results

The estimation strategy adopted here relies on the use of the Arellano–Bond system generalized method of moments (GMM) estimator (47) with robust SEs. A number of nested models are estimated, the most comprehensive of them having the following structure:

$$\begin{aligned}\log(AL_{it}) = {} & \mu + \alpha_i + \gamma_1 \log(AL_{i,t-1}) + \gamma_2 \log(AL_{i,t-2}) + \delta_1[(INEQ) \\ & \times (APROD_{it})] + \delta_2[(INEQ) \times (APROD_{i,t-1})] \\ & + \delta_3[(INEQ) \times (APROD_{i,t-2})] + \beta_1 \log(APROD_{it}) \\ & + \beta_2 \log(APROD_{i,t-1}) + \beta_3 \log(APROD_{i,t-2}) \\ & + \beta_4[\log(APROD_{it})]^2 + \beta_5[\log(APROD_{i,t-1})]^2 \\ & + \beta_6[\log(APROD_{i,t-2})]^2 + \beta_7 \log(\mathrm{EXP}_{i,t-1}) \\ & + \beta_8 \log(\mathrm{EXP}_{i,t-1}) + \beta_9 \log(\mathrm{EXP}_{i,t-2}) \\ & + \beta_{10} \log(RPOP_{it}) + \beta_{11} \log(RPOP_{i,t-1}) \\ & + \beta_{12} \log(RPOP_{i,t-2}) + \beta_{13} \log(GDP_{it}) \\ & + \beta_{14} \log(GDP_{i,t-1}) + \beta_{15} \log(GDP_{i,t-2}) \\ & + \beta_{16} \log(PEDS_{it}) + \beta_{17} \log(PEDS_{i,t-1}) \\ & + \beta_{18} \log(PEDS_{i,t-2}) + \beta_{19} \log(API_{it}) \\ & + \beta_{20} \log(API_{i,t-1}) + \beta_{21} \log(API_{i,t-2}) + v_{it}. \end{aligned} \quad [1]$$

The dependent variable in expression **1** is the natural logarithm of the agricultural area (AL_{it}) in the ith country at time t, and the independent variables include the 1-y and the 2-y lagged dependent variable, the interaction between the natural logarithm of the inequality measure (*INEQ*) and the natural logarithm of agricultural productivity (*APRODit*) in the ith country at time t, the natural logarithms of agricultural productivity ($APROD_{it}$) in the ith country at time t, the squared natural logarithm of agricultural productivity, the natural logarithm of a value index of agricultural export (EXP_{it}) for the ith country at time t, the natural logarithm of the rural population ($RPOP_{it}$) in the ith country at time t, the natural logarithm of the per-capita GDP (GDP_{it}) in the ith country in year t, the natural logarithm of the service on external debt as percentage of GDP ($PEDS_{it}$) in the ith country at time t, and the natural logarithm of the agricultural price index (API_{it}) in the ith country at time t. The 1-y and 2-y lagged values of the explanatory variables are also included. Three measures of inequality, namely, income Gini coefficients ($\mathrm{GINI_i}$ as in model 1, model 2, and model 3), land Gini coefficients ($\mathrm{LGINI_i}$ as in model 4, model 5, and model 6), and wealth Gini coefficients ($\mathrm{WGINI_i}$ as in model 7, model 8, and model 9) are considered.

For space reasons the full estimation results are presented elsewhere (see *SI Appendix*, Table S1, for model 3, model 6, and model 9), alongside those relative to nested versions of expression 1 (models 1 and 2, models 4 and 5, and models 7 and 8 in *SI Appendix*, Tables S2–S4, respectively). The Arellano–Bond difference GMM estimator is also presented for completeness (*SI Appendix*, Tables S5–S7). The use of dynamic panel allows accounting for both the dynamic nature of agricultural expansion and for the endogeneity of a number of explanatory variables (48). In all models the 1-y and 2-y lagged dependent variable are statistically significant, thus suggesting that indeed agricultural expansion in Latin America is a dynamic process.

Of particular interest to the present analysis is the effect of agricultural productivity ($APROD_{it}$). The relevant parameters estimates (a subset of those presented in *SI Appendix*, Table S1) are reported in Table 1. To begin with, consider the case in which income, land, and wealth are evenly distributed (i.e., $\mathrm{GINI_i} = \mathrm{LGINI_i} = \mathrm{WGINI_i} = 0$), so that the interaction between productivity and inequality (*INEQ*) can be temporally ignored. As the coefficient β_1 is positive and in some cases statistically significant (Table 1 and *SI Appendix*, Tables S1–S4), the instantaneous effect of agricultural productivity appears to be

Table 1. Selected parameters estimates for expression 1

	Model 3[†]	Model 6[‡]	Model 9[†]
Variables	INEQ = $GINI_i$	INEQ = $LGINI_i$	INEQ = $WGINI_i$
(INEQ)×($APROD_{it}$)	3.89e-05***	5.02e-06***	1.86e-06***
	(1.44e-05)	(1.85e-06)	(7.02e-07)
(INEQ)×($APROD_{i,t-1}$)	−3.10e-05***	−5.94e-06***	−1.53e-06***
	(1.07e-05)	(2.06e-06)	(5.13e-07)
(INEQ)×($APROD_{i,t-2}$)	5.34e-06	2.03e-06*	2.89e-07
	(6.70e-06)	(1.07e-06)	(3.24e-07)
Log($APROD_{it}$)	0.0199	0.287**	0.0196
	(0.0122)	(0.143)	(0.0122)
Log($APROD_{i,t-1}$)	−0.0143**	−0.524***	−0.0141**
	(0.00639)	(0.194)	(0.00622)
Log($APROD_{i,t-2}$)	0.0114*	0.295**	0.0118*
	(0.00617)	(0.134)	(0.00616)
[Log($APROD_{it}$)]^2	−0.0114**	−0.0460**	−0.0111**
	(0.00565)	(0.0209)	(0.00560)
[Log($APROD_{i,t-1}$)]^2	0.00742*	0.0678***	0.00734**
	(0.00379)	(0.0257)	(0.00371)
[Log($APROD_{i,t-2}$)]^2	0.000541	−0.0294*	0.000364
	(0.00232)	(0.0155)	(0.00227)

See *SI Appendix*, Table S1. Robust SEs are in parentheses. ***$P < 0.01$, **$P < 0.05$, and *$P < 0.1$.
[†]No Suriname.
[‡]No Guyana, Mexico, and Suriname.

moderately associated with agricultural expansion (Jevons paradox). However, such an effect is nonlinear because the coefficient β_5 is negative and also (in most cases) statistically significant. When temporal lags are accounted for, the overall effect of agricultural productivity is in most cases land-sparing (because coefficients β_2 and β_3 are negative, mostly statistically significant, and of greater magnitude than β_1). That is to say, assuming a perfectly even distribution of income, land, and wealth, the instantaneous effect of increases in productivity is to expand agricultural area, whereas the overall effect (accounting for temporal lags) is to contract agricultural area.

Consider now the case in which inequality increases (i.e., $GINI_i$, $LGINI_i$, and $WGINI_i$ take a positive value). To assess the impact of agricultural productivity, the interaction between inequality and productivity must now be considered. How does inequality impact the relationship between agricultural productivity and agricultural area? The instantaneous effect of increases in inequality is denoted by the sign and magnitude of coefficient δ_1. The overall effect of inequality, which accounts for temporal lags, depends also on the magnitude of coefficients δ_2 and δ_3. The results presented in Table 1 (and additionally in *SI Appendix*, Tables S1–S4) indicate that δ_1 is positive and statistically significant and δ_2 is negative (but in absolute value smaller than δ_1) and statistically significant, whereas δ_3 is positive but only moderately statistically significant. It then follows that an increase in inequality ultimately promotes agricultural expansion. To more clearly visualize this result, I compute the instantaneous and overall (i.e., accounting for temporal lags) elasticities of agricultural area with respect to inequality (Fig. 1). Increasing inequality promotes agricultural expansion, with the instantaneous effect being larger than the overall effect. This suggests the existence of a gradual adjustment process. Additionally, the effect of income inequality is also relatively larger than the ones associated with land and wealth inequality.

With respect to the other explanatory variables (as from *SI Appendix*, Tables S1–S4), it is worth discussing the effects of rural population, given the mentioned interplay between demographic pressures and inequality (especially in land distribution). The results show how current and 1-y lag rural population have no statistically significant effect on agricultural area, whereas the 2-y lagged rural population has a moderate and positive effect on agricultural expansion. This suggests the existence of a delay between demographic changes and production decisions, consistent with evidence from Brazil (49) and Ecuador (31). It possibly implies that older settlements are likely to have a larger impact on agricultural expansion as, for example, children of migrant households age to adulthood and contribute to agricultural production expansion. Moreover, the fact that the coefficient associated with the 2-y lag rural population is not statistically significant when inequality is measured through the land Gini coefficient (model 6) hints at an association between land access and demographic pressures (although the pairwise correlation in the sample between $RPOP_{it}$ and $LGINI_i$ is only 0.4).

Discussion

The empirical results indicate that increasing inequality is potentially conducive to agricultural expansion, in a context of increasing agricultural productivity. The magnitude of this effect depends on the specific form of inequality, measured here through income Gini, land Gini, and wealth Gini coefficients and on the length of the temporal horizon considered. The instantaneous effects of increases in agricultural productivity are to

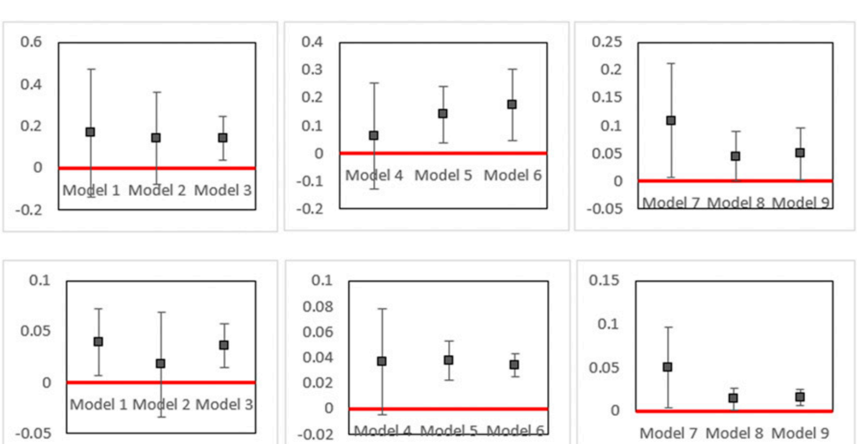

Fig. 1. Estimated instantaneous elasticities (*Top*) and overall elasticities (*Bottom*) of agricultural area with respect to income inequality (*Left*, models 1–3), land inequality (*Center*, models 4–6), and wealth inequality (*Right*, models 7–9). The figure shows the point estimates, calculated when all relevant variables are evaluated at the sample mean, and the 95% confidence intervals.

moderately expand agriculture. The overall effect (accounting for temporal lags) of increases in agricultural productivity is mainly land-sparing. At the same time, increasing income, land, and wealth inequality erodes the land-sparing benefits of increasing productivity, ultimately leading to Jevons paradox. The overall effects of inequality are generally smaller than the instantaneous effects, hinting at the presence of adjustment processes, and the effects of income inequality appear to be slightly larger than those of land and wealth inequality.

Although the exact mechanism through which inequality operates cannot be explicitly examined, the results presented in this article lend themselves to a number of possible interpretations. With respect to the effects of income inequality, it has already been noted that higher inequality may be detrimental to the quality of both political and economic institutions. In Latin America, there is evidence that greater income inequality has allowed economic elites to shape the institutional context to their own advantage, particularly through the access to public lands and natural resources (45). It seems plausible that also other forms of inequality, namely, in wealth and land distribution, are detrimental to the collective action necessary to reap the benefits of increases in agricultural productivity and restrain agricultural expansion (19, 20, 50). For example, empirical evidence among forest communities in the Himalayan region shows how greater equality in the land distribution is positively correlated with a number of collective action initiatives (e.g., community meetings) aimed at promoting forest protection (38). Similarly, field experiments in Colombia have shown how increasing wealth inequality leads to poorer cooperation with respect to harvest decisions in a common forest (37). When looking specifically at land inequality, additional considerations come to mind. An uneven distribution of land may reduce access to land and thus exacerbate the effect of demographic pressures on further agricultural expansion and deforestation (18, 30, 51, 52). Further, agricultural expansion may be easier in areas where land property is concentrated. Acquiring land from many small owners may prove difficult due to excessive transaction costs. For example, the expansion of the agricultural frontier in the states of Mato Grosso and Parà in Brazil over 2000–2005 was characterized by the need of producers to easily access land in areas where land ownership was not excessively fragmented (53). Last, agricultural expansion in Latin America is associated to the production of commodities characterized by increasing returns to scale: only when land property is concentrated enough is the production of such commodities financially viable. For example, the technological package associated with the introduction of genetically modified soybeans in Argentina is particularly suited to large-scale farming and played an important role in the expansion of the crop outside the Pampean region (54).

The methodology employed in this article is appropriate to deal with both the dynamic nature of agricultural expansion and the endogeneity of the explanatory variables. The results have important policy implications. The case for a progressive tax on income and wealth, as a way to curb inequality, has recently been made (35). In Latin America, however, poor access to land is one of the main causes of poverty (55, 56). For this reason, I would like to focus on policies specifically addressing land inequality. One potential intervention could be the introduction or the strengthening of a land value tax (LVT), an idea that is most often attributed to Henry George (57). In the context of agriculture, evidence from the United States indicates that low property and land value tax rates are associated to land concentration (58). Besides having a strong environmental impact, agricultural expansion in Latin America has been also associated to financial speculations and rent-seeking (59), which contribute little to the well-being of local populations. With this knowledge, an LVT would strongly discourage what Veblen referred to as "absentee ownership" and "speculative" acquisition of land (60, 61). On a practical level an LVT would be easier to implement than a tax on wealth because land is more difficult to conceal. At the same time an LVT would significantly address also the problem of wealth inequality because an important portion of wealth in Latin America is stored in land (56). The low correlation between land and wealth Gini coefficients in the sample (−0.0579) is due to the fact that the land Gini has been computed only for agricultural land, thus excluding urban land (a major component of wealth). The introduction of an LVT in Latin America would help to steer the economy away from rent-generating activities (62), would address the increasing concentration of land, and by so doing would help to slow down the process of agricultural expansion in frontier areas. Other potential areas of intervention aimed at improving access to land include better inheritance laws, land reforms, and recognition of aboriginal peoples land rights (55, 63). Finally, given the important role of demographic changes in promoting agricultural expansion in areas with poor access to land, complimentary policies could aim at controlling rural population as a way to ease pressures on remaining forests.

Methods

By drawing on data from the Food and Agricultural Organization (FAO), the World Bank, Credite Suisse (64), and the Standardized World Income Inequality Database (SWIID) (65), panel data are constructed for 10 Latin American countries (Argentina, Bolivia, Brazil, Colombia, Costa Rica, Guyana, Mexico, Peru, Suriname, and Venezuela) over the period 1990–2010 (66). A number of multivariate statistical models are used to explain the determinants of agricultural expansion. Variables reflecting agricultural demand, like per-capita GDP (6), agricultural trade (53), service on external debt (7, 8), and agricultural intensification (43, 67), are accounted for. The effect of various inequality measures is also explicitly examined.

Panel Data Analysis. The use of panel data techniques (68, 69) to assess the determinants of land use cover change (5, 43) allows overcoming the problems associated with cross-section and/or bivariate correlation analysis, which ignore temporal dynamics and uncontrolled factors (70). Panel data consist of a repeated cross-section, including individual units of observations $i = 1 \ldots N$ over a period of time $t = 1 \ldots T$. By using panel data, one can control for unobserved factors that vary across individuals but are constant over time. Given the following statistical model,

$$y_{it} = \mu + \beta_1 x_{1it} \ldots \beta_k x_{kit} + u_{it}, \quad \textbf{[2a]}$$

$$u_{it} \sim N(0, \sigma_u^2), \quad \textbf{[2b]}$$

where y_{it} represents the dependent variable, $x_{1it} \ldots x_{kit}$ represents the vector of k explanatory variables, u_{it} is the error term, and μ and $\beta_1 \ldots \beta_k$ are parameters to be estimated. The error term in [**2b**] can be decomposed as $u_{it} = \alpha_i + v_{it}$, where α_i indicates factors that vary across unit but are constant over time. Expressions **2a** and **2b** can then be rewritten as

$$y_{it} = \mu + \alpha_i + \beta_1 x_{1it} \ldots \beta_k x_{kit} + v_{it}, \quad \textbf{[3a]}$$

$$v_{it} \sim N(0, \sigma_v^2). \quad \textbf{[3b]}$$

To estimate expressions **3a** and **3b**, the one-way fixed-effects (one-way FE) or the one-way random-effects (one-way RE) models can be used (*SI Appendix*). The FE approach is particularly suited when the unobserved components are thought to be correlated with the error term (71).

Dynamic Panel Data Analysis. One particular approach to panel data, which allows accounting also for the effect of past realizations of the dependent and some explanatory variables, is known as dynamic panel data (69). This approach is particularly appropriate for the analysis developed in this article because agricultural expansion is a dynamic process, where past conversion of forest to agricultural uses is likely to play an important role in subsequent conversion.

A dynamic panel specification has two main advantages: first, the presumably dynamic nature of the data-generating process (DGP) is accounted for, thereby allowing for the dependence of the current realization of the dependent variable on its own past realizations, and second, the difference between instantaneous and overall (i.e., accounting for temporal lags) effects of the dependent variable with respect to the explanatory variables of interest can be investigated.

In econometric terms, a dynamic panel regression reads as follows:

$$y_{it} = \mu + \alpha_i + \sum \gamma_k y_{i,t-k} + \beta \mathbf{x}_{it} + v_{it}, \qquad [4a]$$

$$v_{it} \sim N\left(0, \sigma_v^2\right). \qquad [4b]$$

In expression **4a**, $y_{i,t\text{-}k}$ represents the past realization of the dependent variable y_{it}, γ_k indicates the effect of the lagged values of the dependent variable on its current realization, $\mathbf{x}_{it}$ is a vector of explanatory variables (eventually including also lagged values), and $\boldsymbol{\beta}$ is a vector of parameters reflecting the impact of such explanatory variables on the dependent variable.

The Data. The dependent variable in the statistical model is a measure of the agricultural land, as from FAO, for the ith country at time t (AL_{it}). The use of the FAO data allows maintaining consistency with the explanatory variables. Although spatially explicit datasets do exist (10, 72, 73), their adoption would have required matching the dependent variables to the scale of the existing independent variables (i.e., national level). This work is clearly beyond the remit of the article. Agricultural productivity ($APROD_{it}$) is obtained as the ratio between the values of agricultural output at constant prices by agricultural area, as from the FAO. The use of a value-based metric of productivity allows for aggregating across various products categories, while at the same time purging out the effect of price changes (because the metric is computed at constant prices). To account for the effect of agricultural exports, value indices of agricultural exports (EXP_{it}) are collated from the FAO. Data on rural population ($RPOP_{it}$) are collated from the World Bank. To account for the effect of economic growth, per-capita GDP data at constant 2,000 US$ (GDP_{it}) are obtained from the World Bank. Finally, to account for the impact of external debt, the value of the external debt service as percentage of GDP ($PEDS_{it}$) is calculated on the basis of World Bank data. To account for the effect of commodity prices, data on agricultural prices index for the ith country at time t (API_{it}) are collated from the FAO.

The inequality measures include income inequality, land inequality, and wealth inequality. With respect to the wealth inequality, I draw on data from the Global Wealth Databook (64). The data book contains wealth Gini coefficients for several countries but unfortunately only from year 2010. In the empirical analysis, the wealth Gini coefficient varies between countries but is constant over time during 1990–2010 ($\mathrm{WGINI_i}$). Concerning the inequality in land distribution, I draw on Oxfam (36), which in turn relies on existing agricultural censuses. The data on land distribution Gini coefficients are also only available at one point in time. The land Gini variable varies across countries but is constant over time ($\mathrm{LGINI_i}$). Data on net income Gini coefficients ($\mathrm{GINI_{it}}$) at country level for the period 1990–2010 have been retrieved from the SWIID database provided by Frederick Solt. To maintain consistency with the models using land and wealth inequality, in the empirical model the cross-country means of the income GINI coefficients ($\mathrm{GINI_i}$) are employed. Treating inequality as varying across countries but not over time involves strong assumptions, which follow mainly from the paucity of data available. There is, however, evidence that inequality in Latin America has not varied too much (74). Moreover, in the empirical strategy, I use a system GMM estimator because this has been shown to be appropriate in cases where some of the independent variables do not change over time (47, 75). Clearly, the availability of a larger set of data on inequality would have allowed for greater flexibility in the functional form specification.

Estimation Strategy. Before using a dynamic panel data estimation strategy, I test whether the country-specific effect (α_i in expression **3a**) should be treated as a fixed or random effect. The Hausman test rejects the null hypothesis of random effects being an efficient estimator at the 0.1% significance level, thus concluding that the country-specific effects should be treated as fixed. This is important because applying the random-effects estimator in a situation where the true DGP follows a fixed-effects structure would yield inconsistent coefficient estimates. One fixed-effects estimator that can cope with a dynamic DGP is the Arellano–Bond system GMM (48). This estimator is robust to the dynamic panel bias one would be confronted with if traditional fixed effects or pooled ordinary least squares estimation were applied to a panel regression equation including lags of the dependent variable as regressors (76). In system GMM estimation, lagged levels and lagged first-differences of the endogenous and the weakly exogenous explanatory variables are employed as so-called GMM-style instruments, whereas strictly exogenous explanatory variables are employed as standard instruments. In the Arellano–Bond approach, the error term is supposed to be serially uncorrelated, and as such, no second-order autocorrelation should be detected. Having tested for the significance of different lagged effects structures, the final specification includes 1-y and 2-y lags. I estimate several nested models, the broadest of which conforms to the following expression:

$$\begin{aligned}
\log(AL_{it}) = {} & \mu + \alpha_i + \gamma_1 \log\left(AL_{i,t-1}\right) + \gamma_2 \log\left(AL_{i,t-2}\right) + \delta_1\left[(INEQ) \times (APROD_{it})\right] \\
& + \delta_2\left[(INEQ) \times \left(APROD_{i,t-1}\right)\right] + \delta_3\left[(INEQ) \times \left(APROD_{i,t-2}\right)\right] \\
& + \beta_1 \log(APROD_{it}) + \beta_2 \log\left(APROD_{i,t-1}\right) + \beta_3 \log\left(APROD_{i,t-2}\right) \\
& + \beta_4 [\log(APROD_{it})]^2 + \beta_5 \left[\log\left(APROD_{i,t-1}\right)\right]^2 + \beta_6 \left[\log\left(APROD_{i,t-2}\right)\right]^2 \\
& + \beta_7 \log(\mathrm{EXP}_{it}) + \beta_8 \log\left(\mathrm{EXP}_{i,t-1}\right) + \beta_9 \log\left(\mathrm{EXP}_{i,t-2}\right) + \beta_{10} \log(RPOP_{it}) \\
& + \beta_{11} \log\left(RPOP_{i,t-1}\right) + \beta_{12} \log\left(RPOP_{i,t-2}\right) + \beta_{13} \log\left(GDP_{it}\right) \\
& + \beta_{14} \log\left(GDP_{i,t-1}\right) + \beta_{15} \log\left(GDP_{i,t-2}\right) + \beta_{16} \log\left(PEDS_{it}\right) \\
& + \beta_{17} \log\left(PEDS_{i,t-1}\right) + \beta_{18} \log\left(PEDS_{i,t-2}\right) + \beta_{19} \log\left(API_{it}\right) \\
& + \beta_{20} \log\left(API_{i,t-1}\right) + \beta_{21} \log\left(API_{i,t-2}\right) + v_{it}.
\end{aligned} \qquad [5]$$

Three versions of expression **5** and the associated nested models, with three different inequality measures, are estimated. In the estimation, the following variables are treated as endogenous: $\log(\mathrm{AL_{i,t-1}})$, $\log(\mathrm{AL_{i,t-2}})$ $\log(\mathrm{APROD_{i,t-1}})$, $\log(\mathrm{APROD_{i,t-2}})$, $[\log(\mathrm{APROD_{i,t-1}})]^2$, $[\log(\mathrm{APROD_{i,t-2}})]^2$ $\log(\mathrm{RPOP_{i,t-1}})$, $\log(\mathrm{RPOP_{i,t-2}})$ $\log(\mathrm{EXP_{i,t-1}})$, $\log(\mathrm{EXP_{i,t-2}})$, $\log(\mathrm{API_{i,t-1}})$, $\log(\mathrm{API_{i,t-2}})$ $(\mathrm{INEQ}) \times (\mathrm{APROD_{i,t-1}})$, and $(\mathrm{INEQ}) \times (\mathrm{APROD_{i,t-2}})$. The GMM-style instruments are collapsed (i.e., one instrument is created for each variable and lag distance) to reduce the instrument count. All estimations are carried out using the xtabond2 add-in for Stata Version 15 (48). In all cases, I cannot reject the null hypothesis of no second-order autocorrelation (as reported in *SI Appendix*, Tables S1–S4).

Quantifying the Impact of Inequality Through Elasticities. To visualize the effect of inequality on agricultural expansion, I compute the instantaneous and the overall (i.e., accounting for temporal lags) elasticity of agricultural area with respect to the inequality metrics. The use of elasticity is appropriate when variables are expressed in different units (77). Given a scalar function $y = f(x_1 \ldots x_k \ldots x_n)$, the elasticity with respect to x_k is given by $\varepsilon_{x_k} = {}^{\partial \log(y)}/_{\partial \log(x_k)}$, and it reflects the percentage change in y given a 1% change in x_k. On the other hand, the marginal effect of variable x_k on y is given by $ME_k = {}^{\partial y}/_{\partial x_k}$. Given the functional specification in expression **5**, the following relationship between the marginal effect of inequality (ME_{INEQ}) and the elasticity of agricultural area with respect to inequality ε_{INEQ} exists: $\varepsilon_{INEQ} = ME_{INEQ} \times APROD_{it}$. The instantaneous marginal effect of inequality is $ME_{INEQ} = \delta_1$. The instantaneous elasticity is computed as $\varepsilon_{INEQ} = \delta_1 \times \overline{APROD}$ (where $\overline{APROD}$ indicates the sample mean of $APROD_{it}$). On the other hand, the overall (accounting for temporal lags) marginal effects of inequality (and associated SEs) are computed by using the margins routine in Stata Version 15, fixing all of the other relevant variables at the sample mean. The corresponding elasticities are subsequently recovered by multiplying the marginal effect by the mean agricultural productivity $\overline{APROD}$.

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