Policy design for effective and equitable reductions in deforestation emissions

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Abstract

The design of forest conservation policies matters for their environmental and welfare impacts, cost-effectiveness, and distributional consequences. In this paper, we first build a theoretically-founded econometric model of land users' deforestation decisions based on global, spatially-granular data. Second, we use this model to simulate different policies intended to decrease emissions by reducing deforestation. Our analysis shows the large potential of carbon pricing to reduce emissions from deforestation, as well as the substantial hurdle of information asymmetry to achieving that success. We

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find that a perfectly targeted carbon price of \$80/ton CO_2 could reduce global emissions from deforestation by about 32%. In contrast, if the payments were made to all remaining forested land, it would cost multiple trillions of dollars, with only 3% of these payments going to additional emission savings. Even assuming a highly informed policy-maker, information asymmetry increases the cost of reducing emissions per ton of CO_2 by 211% due to both enrolling non-additional land parcels while missing other cost-effective parcels. The problem of non-additionality is particularly large at low carbon prices. Carbon taxes do not require similar targeting efforts and might therefore be a viable alternative but impose large costs on land users in the poorest countries. Emission savings from avoided deforestation largely occur in lower income countries and the poorest decile of land users contributes six times the reduced emissions of the richest. Monetary transfers could mitigate tax-related equity concerns.

1 Introduction

Payments for avoided deforestation have the potential to achieve large reductions in greenhouse gas emissions at a low cost (Busch, Engelmann, et al. 2019; Franklin and Pindyck 2024). However, past payments for avoided deforestation often fail to deliver meaningful changes in deforestation (Börner et al. 2017). In particular, many policies seeking to pay landowners for changes in deforestation behavior have been undermined by inaccurate targeting and an associated lack of additionality (West, Wunder, et al. 2023). This gap between the prospective benefits of payments for avoided deforestation and their observed impacts has undermined enthusiasm for this climate policy (Song 2019). Careful design of forest carbon policies can improve their effectiveness, although empirical evidence is limited (Jack et al. 2008; Kerr 2013; Cattaneo et al. 2010; Grabs et al. 2021).

In this paper, we explore how the choice and design of policies for avoided deforestation affects their environmental and welfare consequences. In contrast to previous empirical estimates of the potential supply of avoided deforestation, we explicitly account for asymmetries in information about the returns to deforestation held by policymakers and land users. This approach enables us to quantify the extent to which non-additionality undermines the cost-effectiveness, equity, and environmental performance of different incentives at global scale.

To simulate global deforestation under alternate policy scenarios, we develop a theoretical model of land users' deforestation decisions in response to economic opportunities (section 2). Our theoretical model explicitly accounts for the heterogeneity in agricultural net returns between land units and that deforestation is constrained by remaining standing forest in the short term. Our model builds upon Van Benthem and Kerr's (2013) theoretical model of deforestation under payments for avoided deforestation in the presence of asymmetric information. We estimate this model econometrically, combining remotely sensed maps of global deforestation (Hansen et al. 2013) with estimates of local returns to agricultural production (Section 2). We then use our estimate of the land supply elasticity to simulate the effect of carbon taxes and payments for avoided carbon emissions under different levels of information on changes in forest cover and carbon (section 3).

We find that a price on carbon emissions from deforestation can achieve large welfare gains. For example, a carbon price of \$80/ton CO_2 could reduce global deforestation emissions between 2021 and 2030 by 32% compared to the counterfactual, yielding a \$515 billion net increase in global welfare if implemented as a payment under full information. However, even with no price on carbon, 93% of the world's forest carbon is unlikely to be released in this period. Therefore, if the policymaker has no information about counterfactual deforestation and provides untargeted payments of \$80/ton CO_2 to all stewards of forests, this would require \$55 trillion in transfers.

Given the large cost of conditional but undifferentiated transfers, payments for avoided deforestation require targeting to improve cost-effectiveness. However, our empirical results highlight that even small information asymmetries are very costly. Modeling a well-informed decision maker who can perfectly discriminate payments at a county level, we estimate that 70% of all payments will be non-additional. In addition, information asymmetries can reduce the environmental benefits of targeted payment programs by discouraging participation by some cost-effective suppliers. In aggregate, at \$80/ton CO_2, we estimate that imperfect targeting would reduce the welfare benefits of carbon pricing by 50%.

In contrast to targeted payments for avoided deforestation, deforestation taxes do not require policymakers to assign land users a baseline level of counterfactual deforestation, eliminating the challenges that emerge from information asymmetries. However, such taxes would shift costs towards land users in lower-income and tropical countries, where most of the emissions from deforestation occur, which raises distributional concerns. We argue that international agreements that provide financial compensation to lower-income countries that adopt domestic deforestation taxes may be an overlooked mechanism to achieve efficient and equitable reductions in carbon emissions from deforestation. Our results show that a redistribution of the simulated carbon tax returns as a lump-sum transfer to land users in the lower income deciles would offset their opportunity costs of avoided deforestation in most of the cases.

By bridging the theoretical (Van Benthem and Kerr 2013) and empirical literature (Busch, Engelmann, et al. 2019) on payments for avoided deforestation, we address an important tension in the current policy debate. Specifically, payments for avoided deforestation have high potential for low-cost abatement (Griscom et al. 2020), but existing payment programs have had little impact on deforestation (West, Börner, et al. 2020). Our model provides an explanation for these two seemingly contradictory patterns: although a large amount of abatement is possible at low costs, the scale of non-additionality due to information asymmetries is also large at low carbon prices. For example, at 2022 voluntary carbon market prices for forest-related credits of \$10 per ton CO_2 (Forest Trends' Ecosystem Marketplace 2023), only 5% of payments yield additional changes in deforestation behavior already at a low level of information asymmetries. However, additionality is increasing in carbon prices – at \$80 per ton CO_2 we estimate that 30% of payments would be additional, while at \$20 per ton, only 10% would be additional.

By linking our estimation model closely to its theoretical foundation, it allows us to estimate welfare impacts unlike previous studies (Busch and Engelmann 2017; Busch, Engelmann, et al. 2019). Moreover, we do this at a global scale and address endogeneity concerns by constructing a potential revenue variable that is assumed exogenous to the deforestation decision (as in Berman et al. 2023; Cisneros et al. 2021).

Our assessment emphasizes the need for precise targeting of payments to land users, providing additional emission savings given that environmental policy budgets are limited. At the same time, payment schemes should not be based on too conservative assumptions about counterfactual deforestation behavior, as this would put the abatement contributions of many land users at risk. Our global analysis adds to existing policy comparisons that focus on specific local contexts (Souza-Rodrigues 2019).

This paper proceeds as follows. In section 2, we first present a theoretical model of land users' decisions to deforest, deriving several theoretical results. We then present the estimation strategy, data and resulting estimates of supply curves for carbon emissions savings. In section 3, we add carbon pricing to our theoretical model to generate results on how carbon taxes and payments for avoided carbon emissions will affect land use, emissions, and welfare. We then present our approach to simulating tax and payments under different levels of asymmetric information, and then present our policy simulation results. In section 4 we present a discussion and conclude in section 5.

2 Empirical model of deforestation

2.1 Theoretical foundation

We assume that land is managed by J land users j, located in region l, each of whom manages N_{jl} units of land, where N_{jlt} is the number of units allocated to forest by user j in region l and year t. The potential returns associated with using unit i for agriculture a, or forest f, in year t, located in region l are given by:

$$r^a_{ijlt} = \mu^a_{jlt} + \xi^a_i, \tag{1}$$

$$r^f_{ijlt} = \mu^f_{jlt} + \xi^f_i, \tag{2}$$

where μ^a_{jlt} is the expected per unit return that would be obtained by land user j across her land portfolio if all of her units of land were devoted to agriculture, μ^f_{jlt} captures the same for forest, and ξ^a_i and ξ^f_i are i.i.d Type-I Extreme Value random variables that represent unit i's fixed characteristics that impact potential returns and are known to land users, such as plot-specific soil quality. If deforesting costs K per unit[1], the net return from clearing a forested plot is given by

$$r_{ijlt} = \mu_{jlt} + \xi_i, \tag{3}$$

where r_{ijlt} is the net return of unit i, μ_{jlt} is the expected potential per unit net return for deforesting land user j's land portfolio if all units were forested ($\mu_{jlt} = \mu^a_{jlt} - \mu^f_{jlt} - K$), and

[1] All heterogeneity between land units, including heterogeneous costs of clearing, is assumed to be absorbed in ξ^a_i and ξ^f_i.

ξ_i is the difference between the two i.i.d Type-I Extreme Value random variables, distributed logistically with location zero and scale normalized to 1. Let F denote the CDF of r_{ijlt} in what follows.

In the standard land allocation problem, land users select the use in each period that provides the highest net return r_{ijlt} (Lubowski et al. 2006). Given our emphasis on deforestation for agriculture, wherein land tends to remain under cultivation for a long time once cleared, we focus on the one-way transition from forest to non-forest use. In this context, it is important to account for the fact that land parcels that are more profitable for conversion (i.e., have larger values of ξ_i) will be converted first, truncating the distribution F and affecting the likelihood of conversion in subsequent periods. Our first result shows how the probability of deforestation varies with the number of forested units N_{jlt} remaining at the beginning of period t:

Theoretical result 1: Assume land users deforest all units for which $r_{ijlt} > 0$ and let $\kappa_{jlt} = N_{jlt}/N_{jl}$ be the fraction of forested units at the beginning of period t in land user j's land portfolio, and $Q(\kappa_{jlt})$ the κ_{jlt} quantile of F. Because the most profitable parcels are converted first, $Q(\kappa_{jlt})$ represents the highest net return among units that are still forested in period t. Land users will only deforest if $Q(\kappa_{jlt}) > 0$, with a probability given by

$$\pi_{jlt} = 1 - \frac{1}{\kappa_{jlt}} \frac{1}{1 + \exp(\mu_{jlt})}. \tag{4}$$

See the demonstration in the Appendix.

Figure 1 illustrates Result 1. The fraction of land units remaining in forest is illustrated on the x-axis, where land units are ordered from smaller to larger net returns, and marginal net returns are shown on the y-axis. Assume we start in $t-1$ with all land units in forest (i.e. $\kappa = 1$). For the purpose of this illustration, assume further that $\mu_{jlt-1} = 0$, and the yellow curve represents net returns across the N_{jl} units. Since $\kappa_{jlt-1} = 1$ and $\lim_{\kappa \to 1} Q(\kappa) = \infty$, the probability of deforestation is given by 1 minus the CDF of r_{ijlt} evaluated at zero with location 0, assumed to equal 0.5 in this illustration. In other words, the land user deforests all units with positive returns —namely, units to the right of the dashed line. In period t, $\kappa_{jlt} = 0.5$, and the relevant distribution for the returns of forested units is truncated at the 50^{th} percentile. If returns to deforestation decrease, i.e. $\mu_{jlt} < \mu_{jlt-1} = 0$, then the remaining forested units have negative net returns since all units with positive values of r_{ijlt} were deforested in the previous period. In this case, illustrated by the red curve, $Q(\kappa_{jlt}) < 0$ and there will be zero deforestation in period t. This is also the case if the expected potential net returns remain unchanged compared to the previous period, that is, $\mu_{jlt} = \mu_{jlt-1} = 0$ and $Q(\kappa_{jlt}) = 0$. If, on the other hand, returns to deforestation increase, $\mu_{jlt} > \mu_{jlt-1}$, r_{ijlt} will be positive for some units, shown by the blue curve, and these land units will be deforested. In this case, $Q(\kappa_{jlt}) > 0$. The probability of deforestation is given by 1 minus the CDF of r_{ijlt} truncated above at the 50^{th} percentile, evaluated at zero with location μ_{jlt}. Graphically, the expected share of deforested units in period t is represented by the horizontal distance between the points where the blue and yellow curves cross the horizontal axis.

Estimation of the empirical model, below, will account for the truncation of F. To avoid a complex likelihood function, it will be convenient to approximate the probability of deforestation, π_{jlt}, with a standard non-truncated logistic function, as shown in the following

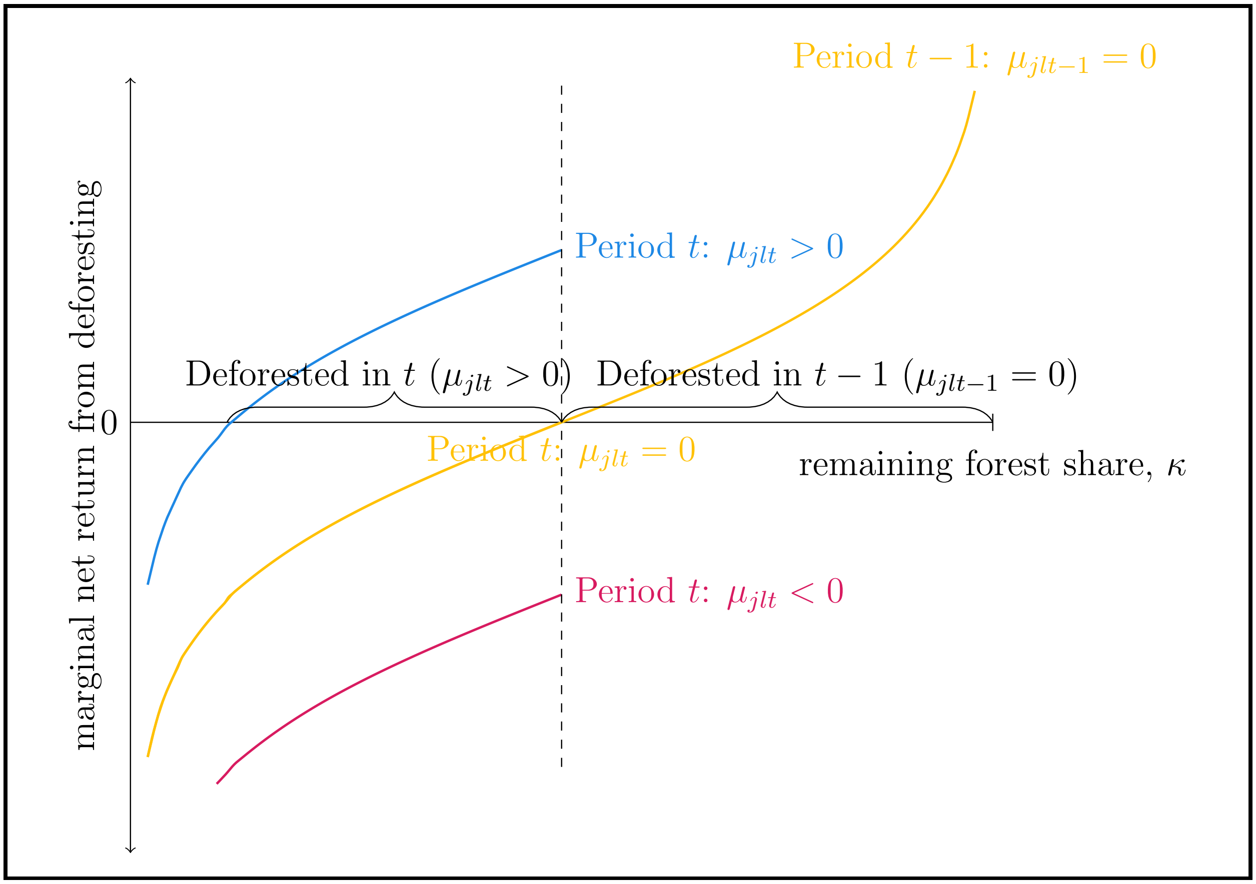

Figure 1: Illustration of Theoretical result 1—The yellow curve represents marginal net returns r_{ijlt} in $t-1$ for land units in the x-axis ordered from smaller to larger net returns when all land units were forested initially (here, remaining forest share = 1 in $t-1$ and thus remaining forest share in $t = \kappa_{jlt} = N_{jlt}/N_{jl}$). The land user deforests all land units with positive returns, located to the right of the vertical dashed line. The blue and red curves represent two alternative scenarios for the net return of deforestation in t. Under the blue line, expected net returns have increased, and the land user deforests an additional fraction of her land. Under the red line, expected net returns have decreased and no further deforestation occurs, as the net return is negative for all land units that remained forested at the beginning of t.

result:

Theoretical result 2: An approximation of π_{jlt} is given by:

$$\tilde{\pi}_{jlt} = \frac{\exp(\nu_j + \eta_1\mu_{jlt} + \eta_2\kappa_{jlt})}{1+\exp(\nu_j + \eta_1\mu_{jlt} + \eta_2\kappa_{jlt})}, \tag{5}$$

where the parameters $\nu_1, \ldots,\ \nu_J,\ \eta_1,\ \eta_2$ minimize the mean square error of a linear approximation to $f(\mu_{jlt}, \kappa_{jlt})$. Given $\tilde{\pi}_{jlt}$ and defining $I_{jt} = \mathbf{1}(Q\left(\kappa_{jlt}\right) < 0)$, the likelihood function that approximates the probability of observing k deforested land units for land user j is given by:

$$Pr(D_{jlt} = k) = \begin{cases} I_{jt} + (1 - I_{jt})\binom{N_{jlt}}{0}(1 - \tilde{\pi}_{jlt})^{N_{jlt}} & \text{if } k = 0 \\ \\ (1 - I_{jt})\binom{N_{jlt}}{k}\tilde{\pi}_{jlt}^{k}(1 - \tilde{\pi}_{jlt})^{(N_{jlt}-k)} & \text{if } k > 0. \end{cases} \tag{6}$$

where D_{jlt} is the count of deforested units. See the demonstration in the Appendix.

To the best of our knowledge, this result provides the first theoretically derived justification for including the remaining standing forest in the specification of the deforestation probability, a common practice in applied research (Busch and Engelmann 2017; Busch, Engelmann, et al. 2019).

2.2 Estimation method and identification strategy

The likelihood function in equation 6 is identical to a standard binomial likelihood with a logistic link function but by introducing I_{jt} it captures the fact that zero deforestation occurs with probability one whenever $\mu_{jlt} < \mu_{jlt-1}$. We account for this zero inflation by estimating a quasi-binomial model (QBM) with likelihood:

$$Pr(D_{jlt} = k) = \binom{N_{jlt}}{k}\tilde{\pi}_{jlt}(\tilde{\pi}_{jlt} + k\phi)^{k-1}(1 - \tilde{\pi}_{jlt} - k\phi)^{(N_{jlt}-k)}, \tag{7}$$

where ϕ is the dispersion parameter and $\tilde{\pi}_{jlt}$ is given in equation 5. Equation 7 is a generalization of a standard binomial model, and accommodates discrete response data that exhibit greater variation than that implied by the binomial model. In our application with relatively small deforestation probabilities, the QBM provides meaningful additional mass at zero.

We use the following parameterization of μ_{jlt} to estimate the model:

$$\mu_{jlt} = \psi_j + \rho_{lt} + \tau R_{jt}, \tag{8}$$

where ψ_j represents a land user specific component of expected benefits to deforestation, ρ_{lt} represents changes in benefits, capturing country-specific policies or economic trends, and R_{jt} is an estimate of the average potential net revenue land user j would obtain in t if all of her land units suitable for agriculture were allocated to crop production. Replacing 8 into 7 yields the following logit link function we estimate for the QBM:

$$logit\,(Pr(D_{jlt} = k)) = \gamma_j + \delta_{lt} + \alpha R_{jt} + \eta_2 \kappa_{jlt}, \tag{9}$$

where $\gamma_j = \nu_j + \eta_1 \psi_j$, $\delta_{lt} = \eta_1 \rho_{lt}$, and $\alpha = \eta_1 \tau$, with ν_j, η_1, and η_2 defined in Result 2. The variable γ_j is a land user fixed effect, δ_{lt} a region-by-year fixed effect (e.g., accounting for time-varying regional changes in agricultural or forestry policies). Data on returns to forestry is sparse. For our estimation, we assume that returns to forestry are constant over time and thus absorbed within land user fixed effects. Note that, as the scale of the logistic link function has been normalized to 1 and R_{jt} is measured in dollars, $1/\alpha$ equals the value of 1 unit of standardized net returns r_{ijlt} in dollars.

Our primary goal is to obtain a causal estimate of α, as this captures land users' deforestation decisions in response to changes in returns to agriculture. To this end, we construct the measure of R_{jt} using plausibly exogenous components of net revenues. Our measure of returns to agriculture, R_{jt}, is calculated as the product of international crop prices and grid cell specific attainable yields less travel time to the nearest port times fuel prices (see equation 10 below). Individual land user's deforestation behavior is unlikely to affect international prices, but local shocks could simultaneously affect local deforestation and local crop prices, if those transmit to international crop prices, which we attempt to capture by country by time fixed effects. Berman et al. (2023) alleviate this concern in a comparable setting. Our estimation strategy requires the assumptions that ports we observe (in the year 2015) have not been built in response to prior deforestation. We use attainable yield data from 2000, which is a projection based on agro-climatic, soil and terrain information, not generated from observed yields, which might be affected by prior deforestation. By including grid cell fixed effects, we capture average yields over time, and our identification only relies on changes in international prices differentially affect local potential agricultural revenues.

One remaining concern is that the effect of changes in agricultural revenue on the decision to deforest might be subject to the security of land property rights. For example, land users might only decide to pursue agricultural investments if they feel that their property rights to this land are secured. We run a robustness check for the subset of our sample for which property rights data are available.

The QBM is estimated using the *fixest* package in R. The model parameters are estimated using iteratively reweighted least squares and the fixed effects are obtained with a fixed-point algorithm described in Bergé 2018. We use Conley standard errors (Conley 1999) to account for spatial correlation with a maximum distance (bandwidth) of 100 km identified using a parametric variogram (see Appendix section 6.2.5). Alternative specifications that have been applied to similar problems do not seem to represent our data well (i.e., the quasi-poisson assumes a principally infinite number of trials) or introduce arbitrary scaling effects (i.e., the inverse hyperbolic sine transformation (e.g. Bellégo et al. 2022; Mullahy and Norton 2022)).

2.3 Data for estimation

Our primary data set is a global annual time-series of tree cover loss between 2001 and 2020 (Hansen et al. 2013). Land user j's portfolio is defined by a 5 arc-minute grid cell (approximately 9 X 9 km at the equator), comprised of up to 96,721 1 arc-second pixels (approximately 30 X 30 m at the equator). The dependent variable in our estimation is the deforestation share relative to remaining forest cover at the end of t-1 (D_{jlt}/N_{jlt-1}), where N_{jt-1} is the number of forested pixels in $t-1$ with at least 25% forest cover, and D_{jlt} is a count of the land units i that are deforested in t. These variables are combined to calculate the number of remaining forested units N_{jlt} in time t and the share of remaining forested units κ_{jlt}.

Potential agricultural revenue R_{jt} is calculated as the weighted sum of attainable crop yields Y_{cj} in 2000 (Fischer et al. 2021) multiplied by annual global prices G_{ct} for each crop c, measured in \$1000 (Bank 2023). Weights are calculated using the harvested area shares H_{ca} by crop within each continental agro-ecological zone a (Monfreda et al. 2008) to compute a weighted sum of the crop-specific revenues. To account for yield increases driven by crop-specific technological progress between 2000 and 2020, we multiply yields by a production index based on global supply changes since 2000 (FAO 2022). The crop price is adjusted by transport costs T_{jt} based on the travel time to the nearest port (Nelson et al. 2019) and global crude oil prices (Bank 2023). Our measure of potential revenues accounts for fixed characteristics of land units (land productivity in 2000, transport distance in 2015) and exogenous temporal variation in crop and fuel prices.

Given that deforestation is not reversible over a short time frame, land users are likely to consider the future stream of agricultural revenues when making decisions of whether to clear the land. Modeling a forward-looking dynamic decision problem is beyond the scope of this study. Rather, we assume that land users have myopic expectations and base decisions on the present discounted value of future revenues, formulated as:

$$R_{jt} = \frac{\sum_c((G_{ct} - T_{jt}) \times Y_{cj} \times H_{ca})}{\iota} \tag{10}$$

where $\iota = 0.05$ is the interest rate (see Plantinga 1996; Lubowski et al. 2006). In equation 10, land users have static revenue expectations, which they update in response to price changes. Agricultural revenues are measured at the farm gate level. We assume complete pass-through of prices along the supply chain (i.e., full competition and market integration at all stages). In a robustness test, we include country-level data on the perceived security of land tenure rights for 2019/2020 (Land Portal and Prindex 2021).

The final dataset includes 20.3 million observations of grid cells that have non-zero forest cover in 2000 and non-zero potential yield for at least one of the included crops. In the fully-specified model, we include 1.02 million grid cell fixed effects and 3,080 country-by-year fixed effects (γ_j and δ_{lt}, respectively, in equation 8). Once all forest in a grid cell is completely deforested, it is removed from the dataset.

2.4 Estimation results

We present estimation results for four versions of the deforestation model (table 1). Model 1, reported in column 1, omits the grid cell and country-by-year fixed effects. Model 2 includes grid cell level fixed effects. Model 3 includes grid cell level and country-by-year fixed effects, but does not control for remaining forest cover, while Model 4, our preferred specification, includes all, remaining forest cover variables, country-by-year and grid cell fixed effects. In all models, as hypothesized, current agricultural revenue has a positive effect on the probability of deforestation. We also observe, consistent with our model, that remaining forest cover increases the probability of deforestation once fixed effects are controlled for.[2] All coefficients on forest cover are significantly different from zero at the 1% confidence level.

Interpreting the estimated revenue coefficient as a semi-elasticity implies that an increase in revenues of \$1000 increases the deforestation share by 2%. This implies that a 16% increase in average revenues results in additional deforestation of about 0.4 hectares (or 0.01%) in a grid cell with the average starting forest cover of 3,468 hectares. Finally, in the versions of the model with grid cell fixed effects (Models 2, 3 and 4), the estimated dispersion parameter ϕ is close to zero, indicating that the standard binomial model provides a good representation of the data despite the truncation at zero (see also equation 7).

Since land property rights are presumably important for the decision to invest in agricultural land and to deforest for this purpose, we test the robustness of the average global

[2]Note that for small values of the deforestation probability π, the estimated coefficients are approximately equal to the semi-elasticity for a given regressor X: i.e., $\hat{B} \approx \frac{\partial \pi}{\partial X} \frac{1}{\pi}$

Table 1: Estimation results for the global Quasi-Binomial Model of deforestation decisions

	Model 1	Model 2	Model 3	Model 4
(Intercept)	$\mathbf{-5.19}^{***}$			
	(0.04)			
revenue	$\mathbf{0.03}^{***}$	$\mathbf{0.06}^{***}$	$\mathbf{0.02}^{***}$	$\mathbf{0.02}^{***}$
	(0.00)	(0.00)	(0.00)	(0.00)
treecover	$\mathbf{-0.30}^{***}$	$\mathbf{0.57}^{***}$		$\mathbf{1.39}^{***}$
	(0.05)	(0.13)		(0.17)
Deviance	548438	262407	243046	242117
Dispersion	0.17	0.02	0.02	0.02
Squared Cor.	0.00	0.24	0.30	0.30
Num. obs.	20337441	20337441	20337441	20337441
FE: grid cell		1020903	1020903	1020903
FE: year & country			3080	3080

Note: Conley standard errors in parentheses. *** indicates significance at the 1% confidence level.

revenue estimate to the perceived security of property rights. Appendix table 3 shows that the estimates are robust to tenure security. Additional heterogeneity tests are provided in the Appendix section 6.2.6.

3 Simulation model of deforestation policies

3.1 Theoretical foundation carbon pricing

Policy makers have several options to induce land users to consider the externalities from deforestation in their land use decisions. Policy makers could introduce a carbon price P and pay land users for avoided carbon emissions. Alternatively, they could tax deforestation at the same rate. In practice, policy makers often set quantitative carbon reduction targets to be reached within a specific time period (e.g., Paris Agreement (UNFCC 2016)). In this paper, we focus on modeling various forms of carbon price instruments to reduce emissions from deforestation. We explore deforestation and carbon impacts under different carbon price levels, accounting for possible information asymmetry between the policy maker and land user.

To model how individuals respond to different policies, we build on the model in Van Benthem and Kerr (2013) and introduce a carbon price into our empirical model of deforestation (section 2). We then use our model to derive the opportunity cost of keeping land in forest incurred by land users, and generate a supply curve for avoided carbon emissions at different carbon prices. This net benefit curve allows us to assess the effectiveness of various policy interventions, such as carbon taxes and payments, under varying assumptions about asymmetric information.

Returning to our empirical model, assume net returns to deforestation are reduced by the price of carbon P. Under a constant average carbon density C_j per land unit in land user j's forest:

$$R'_{jlt} \;=\; R_{jlt} - PC_j. \tag{11}$$

Denote the counterfactual probability of deforestation ($P = 0$) by π^*_{jlt} and the deforestation probability under a positive carbon price by π'_{jlt}, both predicted by equation 9. Then, we have that

Theoretical result 3: An approximation of the opportunity cost L_{jt} under carbon price P for land user j is given by:

$$L_{jtp} \;\approx\; -A_j\kappa_{jlt}\left(\pi'_{jlt}P_pC_j + \frac{1}{\alpha}\log\left(\frac{1-\pi^*_{jlt}}{1-\pi'_{jlt}}\right)\right), \tag{12}$$

where A_j is the average area per land unit suitable for agriculture controlled by land user j and κ_{jlt} the fraction of her land forested at the beginning of period t. See the demonstration of this result in the Appendix.

We illustrate how a carbon price shifts the PDF of net returns from deforestation, r_{ijlt} relative to the shares of remaining forest cover after deforestation within t in figure 2 for a hypothetical land user. Positive carbon prices shift the marginal net return curves down and increase the share of remaining forest. To generate a net benefit curve for avoided carbon emissions, the difference in remaining forest cover could be translated into the embedded avoided carbon emissions E_{jtp} in tons of CO_2 generated under each carbon price.

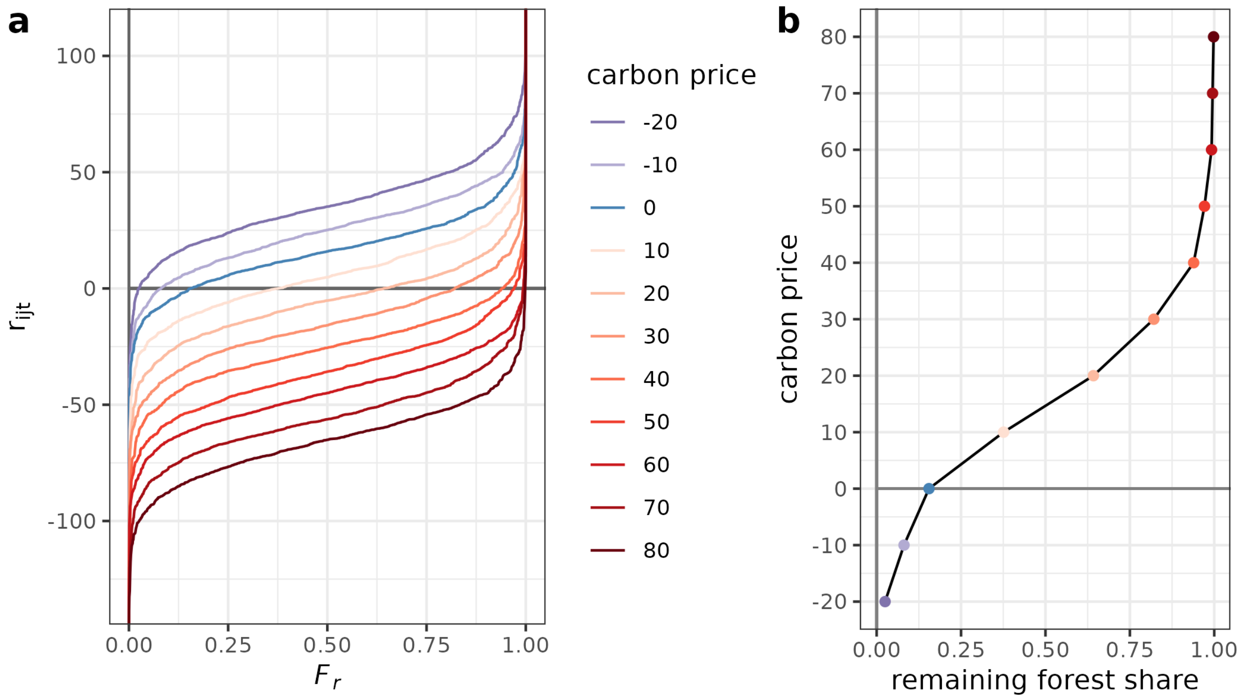

Figure 2: (a) Carbon pricing shifts the marginal net returns curves (net returns r_{ijlt} on the y axis and F_r being the CDF of r_{ijlt} on the x axis); (b) the remaining forest shares under different carbon prices are derived from intersection points at $r_{ijlt} = 0$ in (a)

3.2 Theoretical foundation policy design

We model four policies designs: (i) a carbon tax on deforestation, (ii) a perfectly targeted carbon payment to avoid deforestation, (iii) a universal carbon payment, and (iv) an imperfectly targeted carbon payment due to information asymmetry. The carbon price P can be implemented as a tax on the carbon released through deforestation or as a payment for avoided carbon emissions through avoided deforestation (i.e., payments for ecosystem services). Under the assumption of full information[3], the resulting change in carbon emissions is the same from either a tax or a payment. However, the level and distribution of costs and benefits will differ between policies.

[3]This also requires to assume that there are no other general equilibrium effects that change emissions in other sectors.

In the case of a tax (i), land users need to pay the carbon price P for every ton of released carbon CO_2 from their deforested area. Since land users would not try to pay the tax in the absence of deforesting, there is no adverse selection problem. Only monitoring and enforcement are needed to levy the tax appropriately.

In the case of carbon payments for avoided deforestation, land users are compensated for *not* deforesting land that they would have deforested in absence of the payment. This approach requires the policy makers to know, or estimate, the counterfactual decisions of land users. We initially assume that policy makers have full information about the behavior of the land user in the absence of a carbon price (ii), i.e., they are able to correctly assess the land unit-specific net returns and thus the deforestation behavior under a zero carbon price.

If policy makers do not know the behavior of land users in the absence of the policy, they could offer a payment to all forest land users, no matter whether the user had they had the intention to deforest or not (iii). All land users for whom the net return of deforestation inclusive of the payment is weakly negative for at least one of their land units (i.e. $r_{ijlt} \leq 0$) would participate in the program. Under this policy, every land unit that remains forested receives a payment. Despite the fact that the resulting (additional) carbon savings are equal to those under the previously described policies, the amount of money required for redistribution would be extremely large due to the non-additional payments.

The most realistic payment scenario is one in which policy makers try to assess the counterfactual deforestation behavior given the information available to them, and offer a payment for a specified reduction in carbon emissions (iv). We assume that the exact net returns an individual land user experiences for each unit of land is private information.

Policy makers seeking to influence the land user's deforestation behavior estimate each land unit's net returns with some mean-zero error ϵ_j:

$$\tilde{r}_{ijlt} = r_{ijlt} + \epsilon_j. \tag{13}$$

We assume the policy maker's error is land user-specific and constant over time. Although a policy maker could potentially learn about ϵ_j over time, in practice payment programs are implemented for a period of years without any changes made to the assumed counterfactual level of deforestation.

We assume that policy makers propose a contract based on their estimate of the quantity of deforestation-related emissions of each land user E^{PM}_{jtp*} under a zero carbon price, and a fixed price per ton of avoided emissions generating an offered payment of O_{jtp} to reduce deforestation. If the land user accepts the contract, she will be paid for all the avoided emissions in comparison to the counterfactual. Note that while contracts apply to the full property, users can still deforest portions of their land and receive the payment for the avoided emissions relative to the contract baseline based on counterfactual emissions.

This idea to base payments on projected counterfactuals is established in the voluntary carbon market, although many of these markets project baselines purely on simple historical averages (Teo et al. 2023). In contrast, we assume a relatively well-informed policy maker that explicitly models the economic incentives facing land use decision-makers.

Given this information and their true deforestation plans, the land users respond to the offered payment $O_{jtp'}$ for reducing deforestation to $D_{jtp'}$. Because $D_{jtp'}$ is based on the policy maker's estimate of net returns, the policy maker will over- or underestimate the

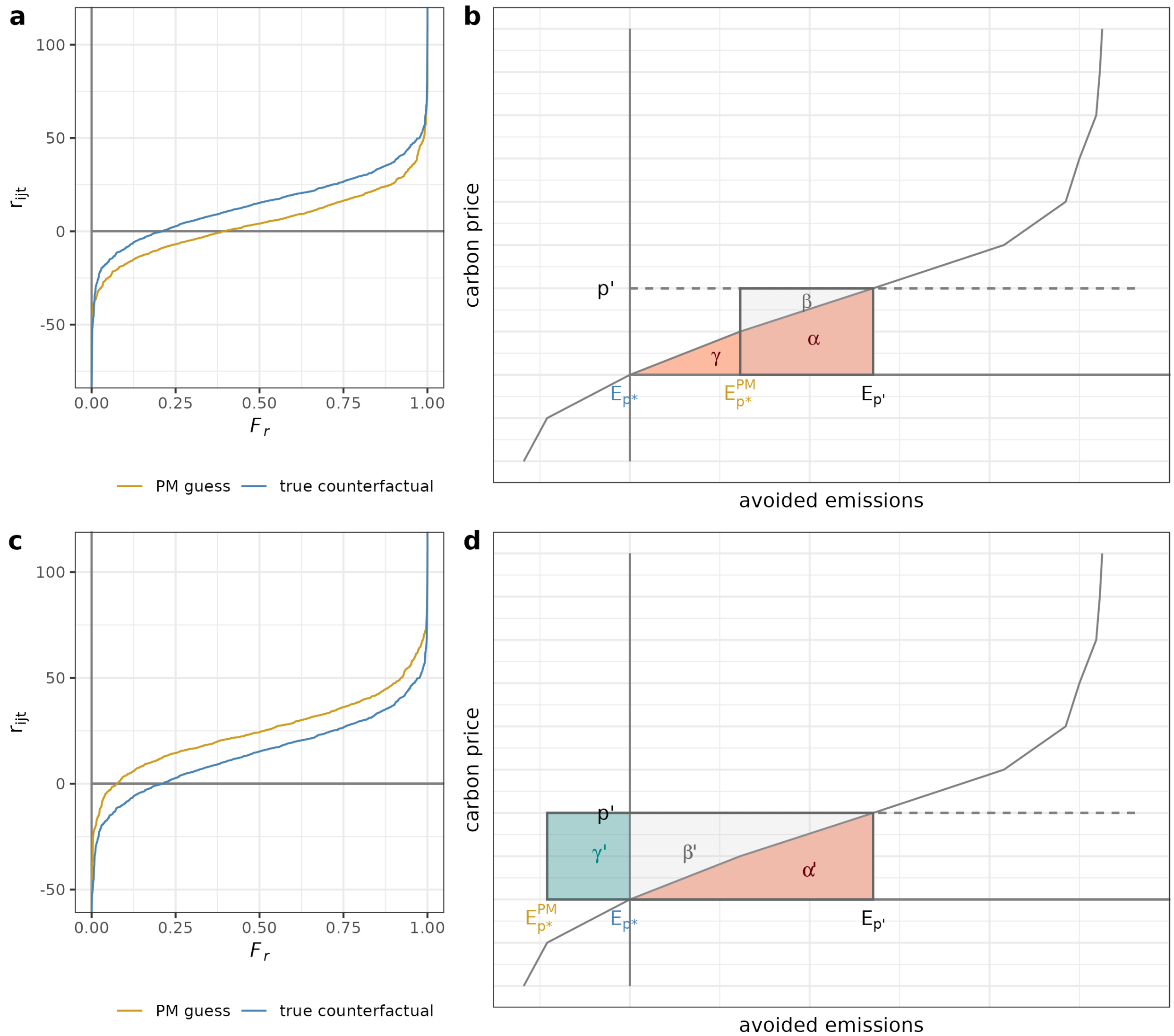

Figure 3: Avoided deforestation and emissions when the policy maker assumes a too conservative (upper panel) or too generous counterfactual (lower panel) for a hypothetical land user. Panel (a) shows the marginal net returns curve at counterfactual and underestimated guess of policy maker (PM). Panel (b) shows the offered payment (O), illustrated as $\alpha + \beta$ given underestimated net returns and opportunity costs (OC), illustrated as $\alpha + \gamma$. Panel (c) illustrates the counterfactual marginal net returns curve and the overestimated guess by policy maker. Panel (d) shows the offered payment ($\alpha' + \beta' + \gamma'$) and the opportunity cost (α') given overestimated net returns and payments for 'non-additional carbon savings' $E_{p*} - E_{p*}^{PM}$

land users' counterfactual deforestation levels. Land users compare the offer to their actual opportunity costs of not deforesting ($L_{jtp'}$). If the offered payment is too low given their true opportunity costs, $O_{jtp'} < L_{jtp'}$, i.e., where the policy maker's guess about the counterfactual is too conservative and the net returns are underestimated by the policy maker, the land user will not participate in the program and instead decide to deforest, such as illustrated in the top panel of figure 3 (a,b). Specifically, they will participate if area $\gamma > \beta$. Thus, some land users who would have beneficially enrolled choose not to participate, reducing both the total payments, and the emissions savings.

Alternatively, the policy maker may overestimate the land users' counterfactual returns from deforestation. In this case, some land users are offered a payment for land units they had not intended to deforest. These land users will opt in to the program and receive a payment for keeping their forest. While paid for, these emissions are not additional (illustrated as $E_{p*} - E_{p*}^{PM}$ in figure 3 c,d). The payment for these 'non-additional emission savings' increases the cost of the policy without achieving additional environmental impact.

3.3 Simulation method

We use our estimated model to predict deforestation shares for each land user under varying carbon prices for the years 2021 - 2030. Analogously to the way we treat potential agricultural revenues, we model taxes and payments for ecosystem services as annualized monetary flows under a 5% discount rate.

3.3.1 Asymmetric Information

Following our model, we simulate asymmetric information by assuming the policy maker does not know the specific time-invariant net return of each land user. As in Bushnell (2011), suppose the policy maker knows the distribution of land user-specific characteristics affecting net returns within each local administrative zone (z), but not where each land user is located in this distribution. We then assume that the policy maker bases the deforestation expectation for each land user on the median of γ_j in a local administrative zone z. To simulate this assumption, we replace the grid cell fixed effects with their medians $\tilde{\gamma}_{jz}$. Ex-post, there is no reason to assume that a policy maker could not also use our non-manipulated model. This exercise shall demonstrate the consequences for avoided emissions arising already from a rather small inaccuracy in the payment targeting.

3.3.2 Endogenous price response

If carbon prices are sufficient to affect the amount of new agricultural land available, we would expect them to also affect the total supply of agricultural commodities and therefore prices. These higher prices for agriculture would then enter into land users decisions to deforest. To capture this price response, we first extract the amount of deforestation predicted in the first year (i.e., 2021) by the model for any given carbon price. Then we transform this amount of deforestation into the implied increase in agricultural supply of each crop associated with these deforested lands. We convert this amount to a percent change by dividing by total production of that crop in the prior year, and then translate it into a percent change in price using the prior year's price as a base (e.g. 2020 prices for 2021) and global demand elasticities from the literature. We then update the price and the implied agricultural revenue for the simulation in the following year. We repeat this process for each year in our simulation. We then compare the trajectory of deforestation (and its implied prices) under no carbon price to that of any carbon price.

For our predictions, year-by-country fixed effects for the 'future' years (2021-2030) are required. Therefore, we regress year fixed effects against a time trend and project year-by-country fixed effects from 2020 for the subsequent years.

3.4 Data for simulation

For the policy simulations, we calculate carbon prices based on the average carbon density per hectare of a land user's forest. For estimates of the carbon contained in each hectare of forest, we apply carbon density data from Spawn et al. (2020). The carbon data comes at 300m resolution for 2010 and we calculate the mean carbon density for each grid cell. These carbon densities are converted to CO_2 and multiplied with the respective global CO_2 price P_p in each scenario. We assume that these prices are set by the policy maker.

To calculate the endogenous price feedback, we combine information on deforestation (Hansen et al. 2013) and land use types (Zanaga et al. 2021; Descals et al. 2021) to approximate how much deforested area ends up being employed in agricultural production. We use global demand elasticities from Roberts and Schlenker (2013). For those crops that are not modeled in their paper, we use an average elasticity. Technological progress is extended until 2030 based on forecasted aggregate crop production (OECD and FAO 2022) and thus exogenous to the carbon price level. Additional data inputs for yields or travel time are taken from the same sources as used in the estimation (see section 2.3). As a comparison to the endogenous price update, we simulate the future impact of the policies based on exogenously forecasted crop price trends from OECD and FAO (2022) and based on fixed prices at 2020 levels.

3.5 Simulation results

3.5.1 Environmental impacts under different policies

In the counterfactual scenario without carbon price intervention, we expect deforestation to emit 33.0 gigatons CO_2 between 2021 and 2030. Under a carbon price around estimates of the level of the global social cost of carbon of \$80/ ton CO_2 (Tol 2023), our simulations show a potential for global carbon savings of 1.6 gigatons CO_2 per year, or 15.8 gigatons CO_2 between 2021 and 2030. The assumed carbon price is close to the 2023 average price in the EU emission trading system of \$90/ ton CO_2, but is considerably higher than in the California cap-and-trade program of \$32/ ton CO_2 (Partnership 2024).

The aggregated quantity of avoided carbon emissions appears to be robust to alternative assumptions of price developments (see Appendix section 6.3). The endogenous price mechanism changes crop prices only slightly compared to 2020 crop prices. This result may alleviate concerns about the potential feedback of carbon pricing on food prices and food security. When introducing a \$80/ ton CO_2 carbon price, we overestimate resulting emission savings by 0.02 gigatons CO_2 when fixing crop prices at 2020 price levels, all else equal, compared to the endogenous price mechanism. In comparison, when using exogenous price trend projections from OECD and FAO (2022), the carbon projected emission savings are by 0.09 gigatons CO_2 smaller.

Total avoided emissions under a carbon price are the same, no matter if implemented as deforestation taxes (scenario i), payments for avoided deforestation under full information (scenario ii) or to all remaining forest (scenario iii). However, the size and distribution of the payments differ substantially under the first three scenarios. Under taxes and full information payments, all avoided emissions are additional (figure 4, a). However, when all remaining forest in 2030 receives a payment under an \$80/ ton CO_2 carbon price, only 3% are paid for (additionally) avoided emissions (figure 4, b).

When introducing asymmetric information (scenario iv), the policy maker has incomplete information about the individual land users' deforestation behavior in absence of a payment. The policy maker underestimates the net returns for half of the land users, making them unlikely to participate in the payment program due to an insufficient payment offer. In figure 5, a, the true supply of additional emission savings is the solid line to the left under asymmetric information, while the dotted line to the right represents the supply curve under full information that includes emissions savings of land users that now opt out of the payment program because their opportunity costs are higher than the offered payment. These land users account for 43% of the predicted carbon savings under full information at a carbon price of \$80/ ton CO_2. This share declines with increasing carbon prices as a smaller fraction of land users opt out of the proposed contract (figure 6, a).

For other land users, the policy maker overestimates their marginal net returns and offers more payments than necessary to ensure their participation, resulting in payments for non-additionality. In figure 5, b, the actual supply of additional emission savings under asymmetric information is again illustrated by the solid line on the right, but the amount paid is represented by the dotted line on the left. As can be observed, the largest increase in non-additional payments occurs just above a zero carbon price, and with increasing carbon price levels, the share of emissions that are non-additional falls (figure 6, b). Intuitively, even at low carbon prices, land users who are offered payments do not deforest land they wanted to keep in forest anyway, would opt in. In contrast, an increase in carbon prices will bring in land users who face a positive opportunity cost of keeping their land in forest.

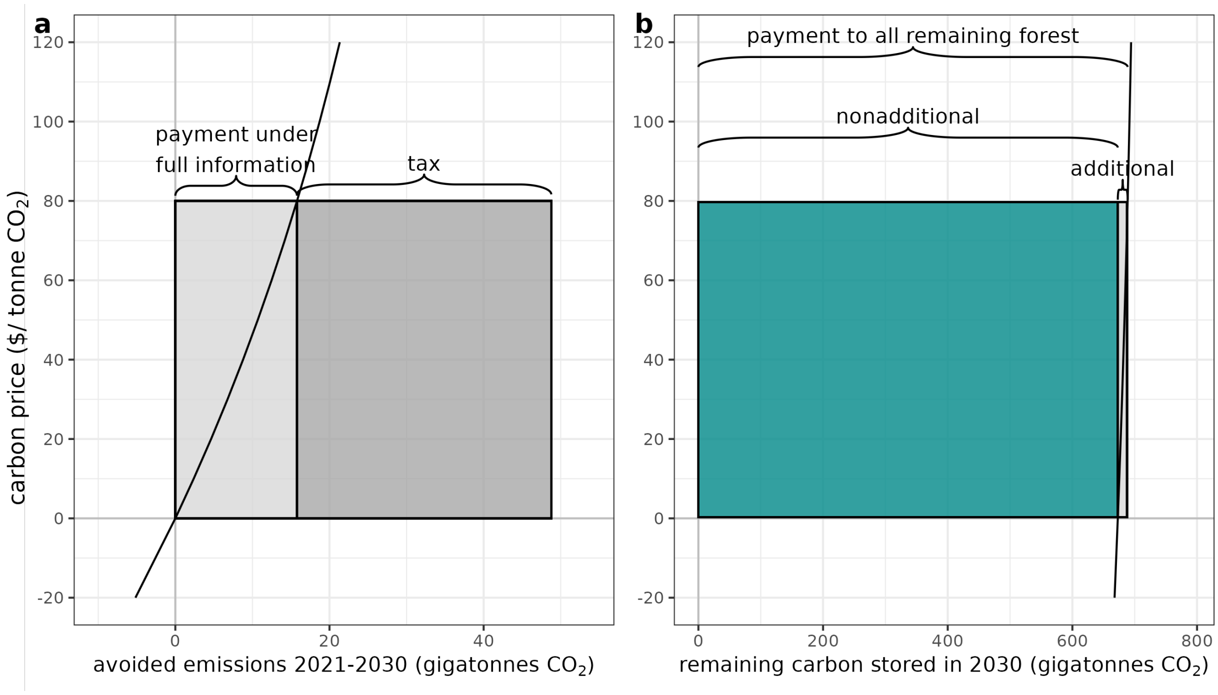

Figure 4: Taxes and payments under \$ 80/ ton CO_2 at global level (a) avoided carbon emissions during 2021-2030 under different carbon prices (abatement cost curve) either generate taxes or require payments for avoided deforestation under the assumption of full information, (b) remaining forest carbon in 2030 under different carbon prices implemented as a payment to all remaining forest implies substantial payments for nonadditionality

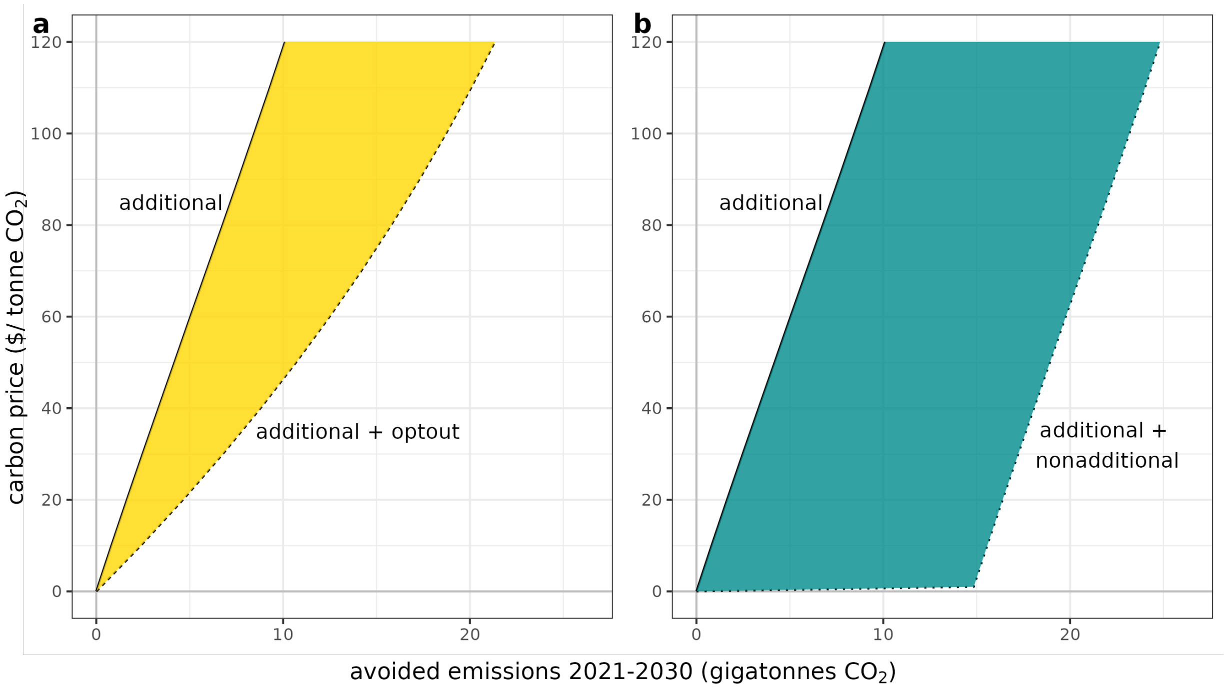

Figure 5: Payment under asymmetric information a) yellow area shows emissions that are not avoided because land users opt out, b) green area shows non-additionality

Figure 6 illustrates the emissions, emissions savings and payments under different carbon prices. Panel (a) shows the total emissions under full information (scenario i) in the dark gray bars, and the emissions savings relative to no carbon price in the light gray bars. As expected, the emissions savings increases with the carbon price. Panel (a) also illustrates the emissions savings under asymmetric information (the brown bars). The difference between the savings under full versus asymmetric information is the emissions lost due to land users opting out because the policy-maker underestimates their deforestation under a zero carbon price, resulting in the offered payment being too low. As expected, the fraction of landowners opting out decreases as the carbon price increases. Panel (b) illustrates the payments made under asymmetric information, and divides them into additional and non-additional. All the non-additional payments occur at low carbon prices, so as prices increase, the new emissions reductions brought in by the higher prices are all additional. Thus, the fraction of non-additional payments decreases as the price of carbon increases. At high carbon prices, further additional emissions savings arise from land users that have opted out under low carbon prices. In these cases, the policy maker still underestimates the amount of savings, but the payment offer nonetheless exceeds their opportunity costs. For these land users, the additional emissions savings exceed the amount paid for (represented by the light blue bar being lower than the sum of the brown and dark blue one in Panel (b)).

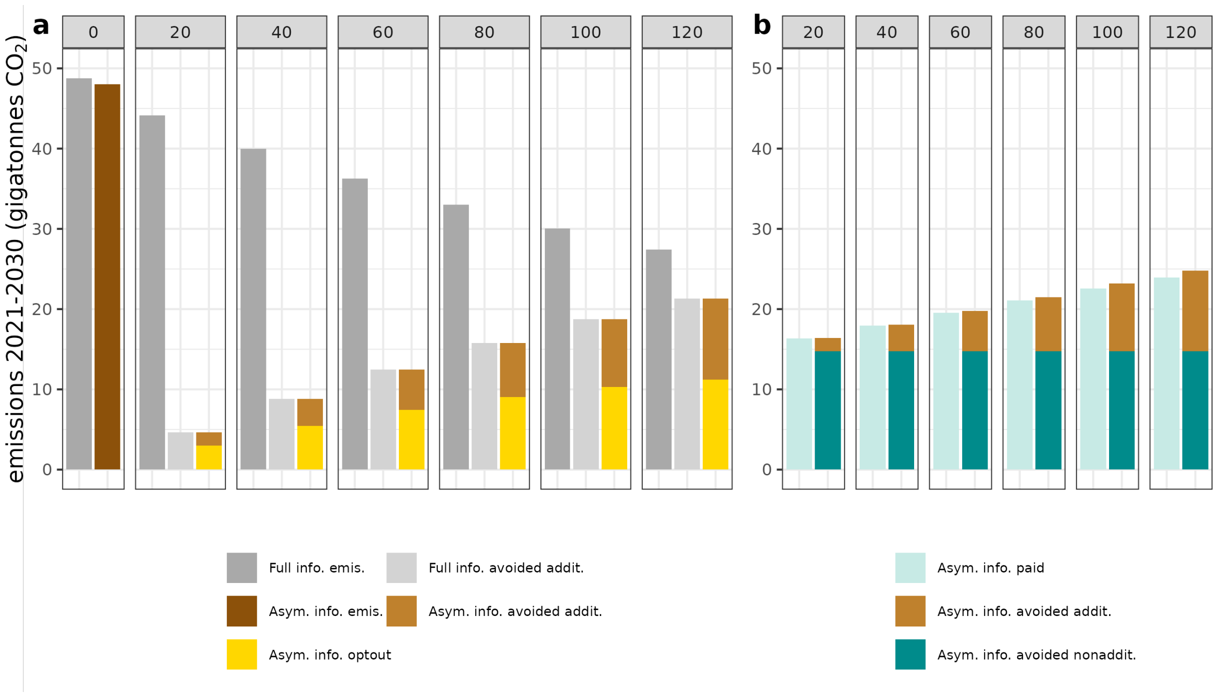

Figure 6: Carbon emissions assuming payments under full or asymmetric information for different carbon prices per ton of CO_2. Panel (a) the amount of additional emissions savings under full information, under asymmetric information, and those emissions that would have been avoided if land users had not opted out due to the offers being too low. Panel (b) illustrates the payments made under asymmetric information in total, and split between those payments that are additional and non-additional.

3.5.2 Cost effectiveness and equity

The level and distribution of monetary transfers is affected by the chosen policy design. Table 2 summarizes aggregated changes in emissions, government spendings, and welfare changes under different policies for a \$80/ ton CO_2 carbon price. It also shows the average cost effectiveness in terms of additionally avoided emissions per \$1 spent as government payments to land users or as tax payments from land users under a \$80/ ton CO_2 carbon price. A payment under full information would require about $1,293 billion of government payments. In this scenario, 0.012 tons of CO_2 are uniformly saved per $. We calculate the change in overall welfare, by multiplying the additionally avoided emissions with the social cost of carbon of $80/ ton CO_2 and then deducting the aggregated opportunity costs of land users avoiding deforestation. Taxes and payments are not considered here. Thus, welfare changes are equal in all scenarios except for the payment under asymmetric information. The payment under full or no information and the tax create additional welfare of $515 billion.

Table 2: Avoided emissions and government balance at $80/ ton CO_2

	FI payment	payment to all	AI payment	tax
add. avoided emis. (GT)	15.786	15.786	6.759	15.786
nonadd. 'avoided' emis. (GT)	0.000	673.914	14.729	0.000
opted out emis. (GT)	0.000	0.000	9.027	0.000
government balance ($ bill.)	-1262.908	-55091.461	-1685.309	2639.121
average cost effectiveness (T/$)	0.012	0.000	0.004	0.006
welfare change ($ bill.)	514.883	514.883	254.602	514.883

Note: FI= Full Information, AI = Asymmetric Information, GT= Gigatons, T= Metric Tons

If the payment was made to all global forested land remaining in 2030, the required government spending would be about $55 trillion at this carbon price. More than 97% of the spending would be paid for 'non-additional emission savings' (as was shown in figure 4, b). Avoided emissions per $1 are very close to 0 tons CO_2 across land units. Under asymmetric information, payments of $1,685 billion are spent by the policy maker at this carbon price but nearly 70% are paid for 'non-additional savings', which reduces the cost-effectiveness in terms of additionally avoided tons CO_2 compared to the payment under full information. Also, the net increase in welfare is reduced to $255 billion, about half of the welfare change under the other policies.

Under the $80/ ton CO_2 carbon price, a tax is on average less cost effective than a payment under full information, but achieves more mitigation per $1 spent than the payments under asymmetric information. Of course the tax is paid for by landowners to governments while the reverse is true for the payments that they receive. From a government perspective, the tax payments would be budgeted as government revenues. For land users who deforest despite the carbon price, the tax reduces their welfare gains from deforestation. For other and potentially poorer land users, the deforestation tax might be prohibitively high, leaving land users with their opportunity costs of the foregone agricultural investment. Where the tax raises equity concerns, the payment can generate revenue opportunities for poor land users, particularly in the absence of information asymmetries.

In our simulations, a large share of the avoided emissions occurs in lower-income countries. To evaluate distributional and equity concerns, we use data from a global gross domestic product (gdp) data (Kummu et al. 2019) and differentiate policy burdens by gdp deciles. Figure 7 shows opportunity costs and tax payments by globally defined gdp decile based on sub-national gdp levels in 2000. The decile with the lowest gdp contributes more than 6 times the emission savings of the decile with the highest gdp under an $80/ ton CO_2 carbon price. Under a carbon tax, the poorest decile faces aggregated opportunity cost around $140 billion for their avoided deforestation between 2021 and 2030.

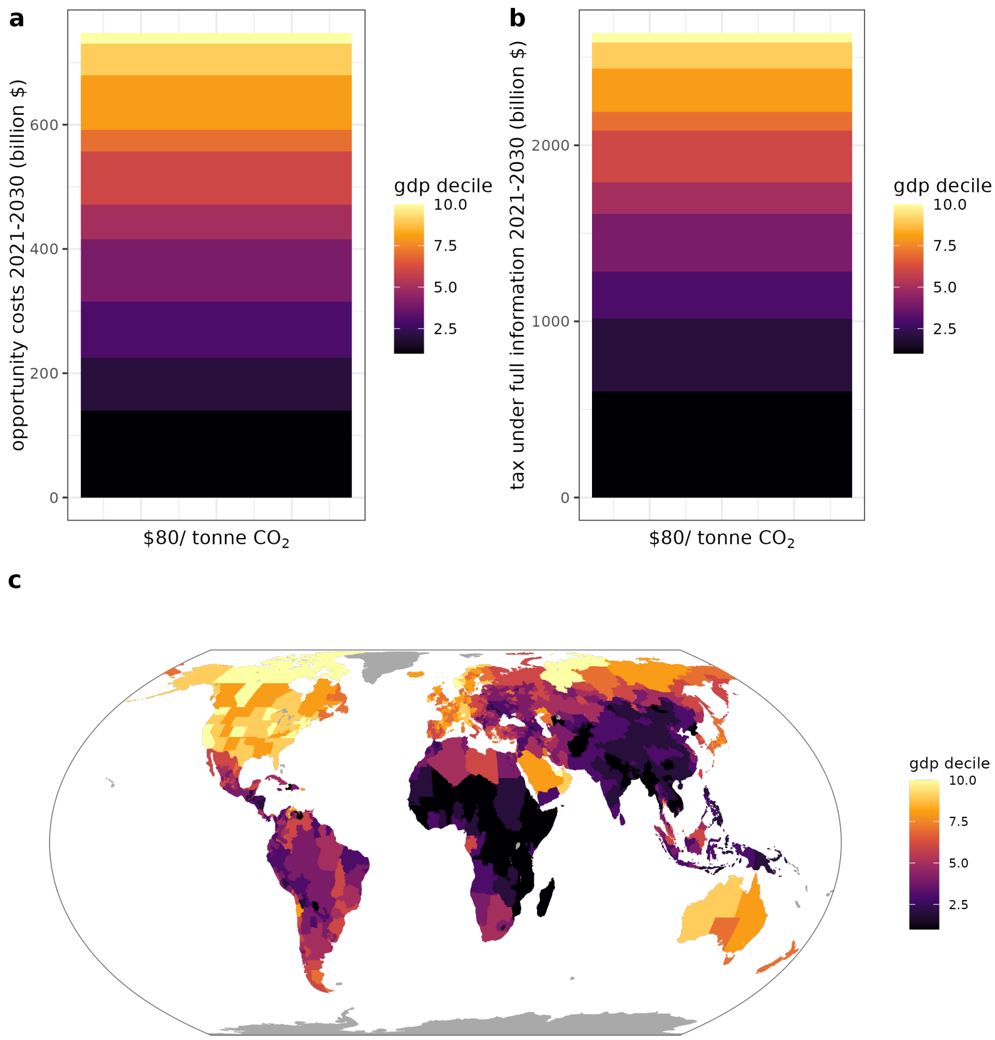

Figure 7: Tax burdens by gdp decile (a) opportunity costs and (b) tax payments under \$80/ ton CO_2 carbon price by (c) gdp decile (globally defined based on gdp levels in 2000 from Kummu et al. (2019))

While the poorest decile avoids most emissions, it also remains the largest contributor of emissions from deforestation and thus pays the largest tax burden of all deciles. While taxes reduce the welfare gains that can potentially be obtained from agricultural production on newly deforested land, the level of tax payments also serves as a lower bound of the agricultural revenues[4].

Nonetheless, in comparison to the counterfactual without carbon pricing, revenues from deforestation are reduced for all land users. For some land users especially in poorer regions, deforestation-related revenues can be an important income source and the only opportunity to escape poverty. A potential lever to reduce these equity concerns related to the tax implementation could be a lump-sum transfer to land users living the regions of the lower gdp deciles.

As an example, the $2,639 billion collected from the carbon tax, could be redistributed equally to the 517,092 land users related to the five lower gdp deciles, resulting in a transfer of about $5 million each after the project period has finished (in this case, after 2030).

For most of these land users, these transfers would offset their opportunity costs from avoided deforestation. For a few land users with extremely high opportunity costs (i.e., land users with very carbon-dense forests and high expected net revenues), the lump-sum transfer is not enough to cover their opportunity costs. Also, those land users that have not avoided a lot of emissions would receive the transfer. A worry might be, that the transferred money could lead to increased deforestation in the following period by land users whose deforestation activity has been capital-constrained beforehand. Nonetheless, the lump-sum transfer to poorer regions helps to address equity concerns and provides an alternative source of income for these land users that can be used in deforestation-unrelated ways. In contrast to the payment for avoided deforestation, there is no need to establish a counterfactual baseline, no worry about non-additionality and the funding of the transferred money is guaranteed

[4] Our data only provides us with the average expected revenues for a land user, but we have no information about the plot-specific revenues. The fact that land users deforest implies for those plots that revenues are higher than the imposed tax.

by design.

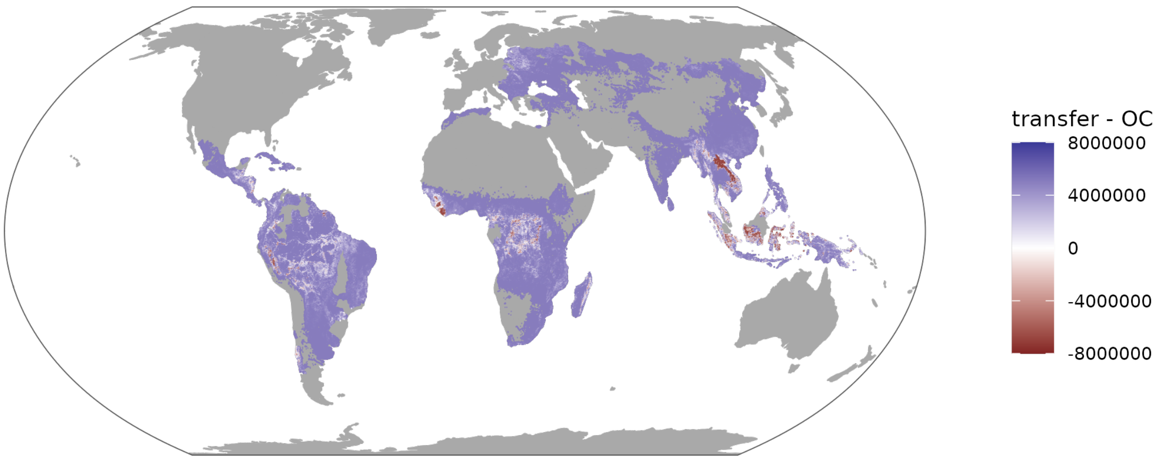

Figure 8: Lump-sum transfer to land users in lower gdp deciles offset opportunity costs (OC) for most land users

4 Discussion

Unlike earlier papers that focus on the tropics, we estimate global potential supply of avoided carbon emissions from deforestation. To better capture the nature of deforestation data, we use the share of deforestation in remaining forest cover instead of the deforestation count or its share in the grid cell area as the dependent variable. Lastly, we address endogeneity by instrumenting revenue in a way that allows us to simulate policies at different carbon prices.

Our estimates of the supply of emission savings under a perfectly targeted carbon price are similar, but a bit smaller than those reported in Busch, Engelmann, et al. (2019) and Busch and Engelmann (2017). Specifically, the emission savings we estimate under a \$80/ton CO_2 are about one gigaton CO_2 per year smaller. These fall even further when we simulate asymmetric information.

Our analysis is based on the assumption that land users are rational, profit-maximizing agents. At the same time, grid cell fixed effects mimic land users' general deforestation preferences and/ or costs. Due to the lack of actual spatial forest property data, the grid cell scale of our data provides only a rough approximation of the true decision making unit. All policy results require that property rights and the discussed policies are enforced and implemented efficiently. Nonetheless, our robustness test stresses that, despite differences in perceived security of land property rights, we find a robust effect on the change in deforestation in response to a change in revenues.

Especially at the global scale of this analysis, implementing such a tax or payment policy would require major coordination efforts by governments and international institutions. Implementation problems arising from weak institutions and corruption, for example, are not directly accounted for in our analysis, apart from those effects that are related to in average deforestation rates, and thus are captured in fixed effects. Transaction costs could differ by policy; taxes would 'only' require monitoring and enforcement, whereas (targeted) payments require the calculation of and agreement on a payment offer based on assumptions of unobserved, counterfactual behavior. In case of taxes, tax revenues could partly refinance the implementation efforts, unless the money is redistributed to address equity concerns. Under all policies, transaction costs could be high given the assumed detailed spatial scale in our assessment. Differences in forest coverage and in (actual) property sizes imply heterogeneous transaction costs at country level. In addition, actual land tenure rights would affect implementation and transaction costs in various ways. Where land tenure rights are unclear, the need for monitoring is even higher as illegal deforestation can only be taxed if the perpetrator is caught. Equally, the payments would be difficult to implement where the legal recipient is unclear.

Our analysis has not only assumed, that land tenure rights are enforced, but also that there is a symmetric response to carbon pricing policies across land ownership types. The contractor and land user in our analysis do not necessarily need to be individual private agents, but could also be a community or other collective forest holder. Public lands can be affected by financial (dis-)incentives in a similar way and are not automatically conserved. Local governments could decide to convert the land in the pursuit of other policy goals, similarly driven by potential (agricultural) revenues. Also, the discussion around voluntary carbon credit schemes could expose public lands to comparable incentives as private land owners. However, it shall be pointed out, that our assessment is not capturing any consequences of a (voluntary) carbon credit scheme. The trade and leakage problems related to such a scheme have not been investigated in this paper. In contrast, the presented results necessarily assume that the same carbon price is affecting deforestation decisions at global scale.

Given that agricultural expansion is one of the main drivers of global deforestation (Curtis et al. 2018), agricultural revenues serve as a good proxy for deforestation responsiveness. However, deforestation for other reasons e.g., timber or cattle production are only captured in as much as their potential revenues are correlated with agricultural products. Thus, our analysis likely underestimates the responsiveness of deforestation to potential carbon payments in some areas. Finally, our predictions for future years do not account for changes in population, preferences or economic growth.

5 Conclusions

Carbon pricing can lead to dramatic increases in carbon sequestration in the world's forests. Although payments for avoided deforestation have been a popular policy recommendation, our analysis highlights the large cost that full payment would incur. In response, many policies have sought to target payments towards additional actions. However, we show that information asymmetries are likely to undermine many targeting efforts. On the one hand, conservative assumptions about land users' counterfactual deforestation provide insufficient incentives for many land users to participate in the payment program. Their additional contributions to avoided emissions would be foregone. On the other hand, too generous assumptions about counterfactual deforestation induce payments for non-additionality. This implies a loss of budget for environmental policies without actual abatement and is getting increasingly problematic if these non-additional emissions reductions would enter the offset market.

In contrast, carbon taxes do not require such an assessment and can therefore be considered a viable alternative. Nonetheless, if the burden of opportunity costs is largely carried by land users in lower-income countries, monetary transfers may be used to mitigate these equity concerns. For example, a lump-sum transfer of tax revenues to land users located in lower-income countries would offset their opportunity costs from avoided deforestation in most cases.

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6 Appendix

6.1 Demonstration of theoretical results

<u>Demonstration of Result 1</u>: As $Q(\kappa_{jlt})$ is the quantile of the land unit with the highest net return among forested units, the result that there will be zero deforestation if $Q(\kappa_{jlt}) < 0$ follows from the assumption that land users only deforest units with positive net returns.

Conditional on deforesting, the fraction of forested units that are deforested—i.e. the probability of deforestation—is given by the mass of units with positive returns among those that are forested:

$$\begin{aligned}
\pi_{jlt} &= \frac{1}{\kappa_{jlt}} \int_0^{Q(\kappa_{jlt})} f(x|\mu_{jlt})dx && (14)\\
&= 1 - \frac{1}{\kappa_{jlt}} \int_{-\infty}^{0} f(x|\mu_{jlt})dx && (15)\\
&= 1 - \frac{1}{\kappa_{jlt}} \frac{1}{1+\exp(\mu_{jlt})}. && (16)
\end{aligned}$$

where $f(x|\mu_{jlt})$ is the logistic pdf with location μ_{jlt}. Equation 15 uses the fact that the probability of the truncated distribution across its support integrates to 1, while equation 16 evaluates the logistic CDF at zero for location μ_{jlt}.

Demonstration of Result 2: Consider the equality

$$\frac{\exp(f(\mu_{jlt},\kappa_{jlt}))}{1+\exp(f(\mu_{jlt},\kappa_{jlt}))} = 1 - \frac{1}{\kappa_{jlt}} \frac{1}{1+\exp(\mu_{jlt})}. \tag{17}$$

Applying the logit function at both sides of the equality and solving for $f(\mu_{jlt},\kappa_{jlt})$:

$$f(\mu_{jlt},\kappa_{jlt}) = \log(\kappa_{jlt}(1+\exp(\mu_{jlt})) - 1). \tag{18}$$

The linear function in (μ_{jlt},κ_{jlt}) that minimizes the expected square distance to $f(\mu_{jlt},\kappa_{jlt})$, given a continuous join distribution of (μ_{jlt},κ_{jlt}), is given by

$$f(\mu_{jlt},\kappa_{jlt}) \approx x_{jlt}\Theta, \tag{19}$$

where $x_{jlt} = (e_j, \mu_{jlt}, \kappa_{jlt})$, e_j is the j-th standard basis vector in $\mathbb{R}^J$, and

$$\Theta = (\nu_1, \ldots, \nu_n, \eta_1, \eta_2)' = E(x'_{jlt} x_{jlt})^{-1} E(x'_{jlt} f(\mu_{jlt}, \kappa_{jlt})). \tag{20}$$

Hence, we obtain the following approximation for π_{jlt}:

$$\tilde{\pi}_{jlt} = \frac{\exp\left(x_{jlt}\Theta\right)}{1 + \exp\left(x_{jlt}\Theta\right)} = \frac{\exp\left(\nu_j + \eta_1 \mu_{jlt} + \eta_2 \kappa_{jlt}\right)}{1 + \exp\left(\nu_j + \eta_1 \mu_{jlt} + \eta_2 \kappa_{jlt}\right)}. \tag{21}$$

Given this approximation, the approximate likelihood of observing k deforested units for land user j in year t is given by a standard binomial distribution with probability $\tilde{\pi}_{jlt}$, tweaked to reflect the fact that deforestation equals zero with probability one if $Q(\kappa_{jlt}) < 0$:

$$Pr(D_{jlt} = k) = \begin{cases} I_{jt} + (1 - I_{jt})\binom{N_{jt}}{0}(1 - \tilde{\pi}_{jlt})^{N_{jlt}} & \text{if } k = 0 \\ (1 - I_{jt})\binom{N_{jt}}{k}\tilde{\pi}^k_{jlt}(1 - \tilde{\pi}_{jlt})^{(N_{jlt} - k)} & \text{if } k > 0, \end{cases} \tag{22}$$

where $I_{jt} = \mathbf{1}(Q\left(\kappa_{jlt}\right) < 0)$.

<u>Demonstration of Result 3</u>: Let π^*_{jlt} and π'_{jlt} represent the predicted probability of deforestation under carbon prices zero and P_p, given by equation 7. We approximate the theoretical quantile function of net returns with the empirical quantile function given by equation 5 to obtain an approximation to the opportunity cost of complying with carbon price P_p.

The marginal net returns given average net returns $\mu^*_{jlt} = \gamma_j + \delta_{lt} + \alpha R_{jt} + \eta_2 \kappa_{jlt}$ at probability of deforestation π_{jt} is approximated by the $1 - \pi_{jt}$ quantile of the empirical distribution of net returns:

$$\tilde{B}(\pi_{jlt}, \mu^*_{jlt}) \;\; = \;\; \mu^*_{jlt} + \log\left(\frac{1-\pi_{jlt}}{\pi_{jlt}}\right). \tag{23}$$

This benefit is expressed in units of the standardized return. As the logistic function scale parameter has been normalized to 1 and the returns R_{jt} are meassured in dollares, the dollar value of one standardized unit of the net return is given by $\frac{1}{\alpha}$. Hence, the marginal benefit from deforestation in dollars equals:

$$B(\pi_{jlt}, \mu^*_{jlt}) \;\; = \;\; \frac{1}{\alpha}\left(\mu^*_{jlt} + \log\left(\frac{1-\pi_{jlt}}{\pi_{jlt}}\right)\right). \tag{24}$$

The opportunity cost of complying with carbon price P_p, $l_{jt}(P_p)$, follows from integrating this expression from π^*_{jlt} to π'_{jlt}:

$$\alpha l_{jt}(P_p) \;\; = \;\; \mu^*_{jlt}\pi - \log(1-\pi) + \pi\log\left(\frac{1-\pi}{\pi}\right)\Bigg|_{\pi^*_{jlt}}^{\pi'_{jlt}}. \tag{25}$$

Noting that $\tilde{B}(\pi^*_{jlt}, \mu^*_{jlt}) = \tilde{B}(\pi'_{jlt}, \mu'_{jlt}) = 0$ and rearranging:

$$l_{jt}(P_p) \;\; = \;\; \pi'_{jlt}P_pC_j + \frac{1}{\alpha}\log\left(\frac{1-\pi^*_{jlt}}{1-\pi'_{jlt}}\right), \tag{26}$$

where C_j is carbon density for grid-cell j. As the total area has been normalized to one, the expression above represents the opportunity cost per hectare that was not deforested due to having carbon price P_p. Then, the total opportunity cost is given by:

$$L_{jt}(P_p) \quad = \quad A_j \kappa_{jlt} \left(\pi'_{jlt} P_p C_j + \frac{1}{\alpha} \log \left(\frac{1 - \pi^*_{jlt}}{1 - \pi'_{jlt}} \right) \right), \tag{27}$$

where A_j is the total land suitable for agriculture of land user j and κ_{jlt} the fraction of remaining forest at the beginning of period t.

6.2 Data preparation, estimation and robustness checks

6.2.1 Deforestation

We extract deforestation from the global forest watch data products on google earth engine. The data is described in Hansen et al. (2013) and was updated for the following years. We classify pixels as forest if their initial forest cover exceeds 25% in 2000. We extract deforested pixels (1 arc-second resolution) if they have been classified as forest. Similarly, we extract forested pixels for the year 2000 subject to the same minimum forest cover threshold. For initial forest cover and deforestation, we sum up the number of pixels that are forested in 2000 or deforested by year, respectively, within our larger-scale grid cells (5 arc-minutes resolution).

The original data product contains information of the initial tree cover share in 2000 for each 1-arc second pixel. We use this information for the inclusion criteria of initially forested pixels. Deforestation counts and shares in remaining forest cover are calculated based on 'full' pixel counts.

6.2.2 AEZ for harvested area shares

To aggregate crop-specific revenues, we create harvested area shares within each continental global agro-ecological zones. By interacting continents with 57 agro-ecological zone groups, we group the (forested) grid cells into 216 categories, displayed in the map in figure 9.

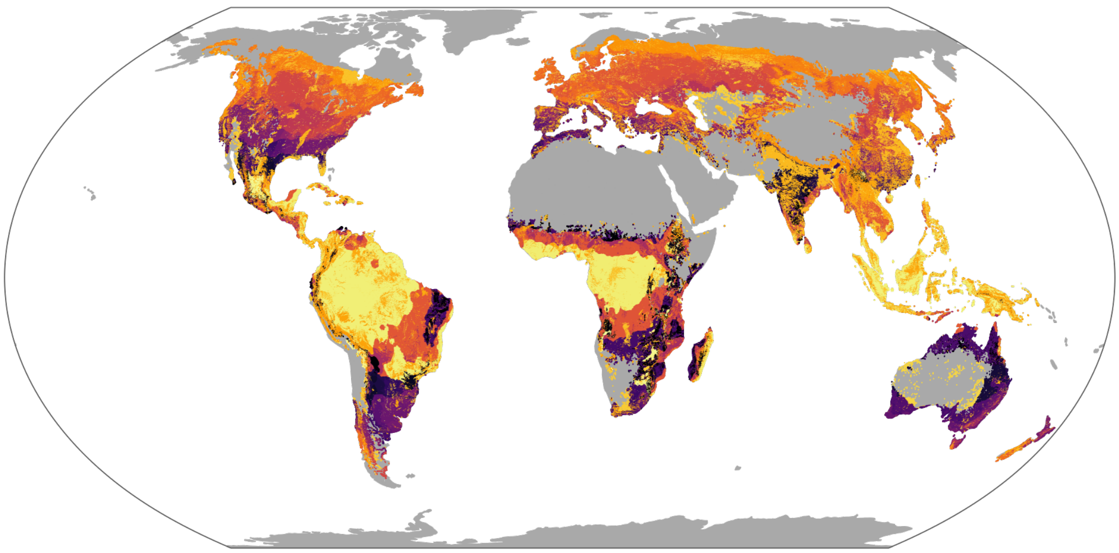

Figure 9: Included grid cells are grouped into 216 continental agro-ecological zones

6.2.3 Transport costs

Transport costs are supposed to reflect market integration. Especially since our revenue variable is based on international agricultural prices, we assume that integration in international markets matters for the effect we estimate. We construct transport costs as follows:

The revenue contains travel costs based on crudeoil prices:

$$R_{jt} = \frac{\sum((G_{ct} - T_{jt}) \times Y_{cj} \times H_{ca})}{0.05} \tag{28}$$

with

$$T_{jt} = oilprice_t * fuelcon * speed * factor/truckload/60 * traveltime_j \tag{29}$$

based on converted crudeoil prices

$$oilprice_t USD/liter = oilprice_t USD/bbl/45 \tag{30}$$

as about 45 liters of diesel (i.e., 12 gallons 3.78 liters per gallon) can be produced from one 42-gallon barrel of crudeoil [5]. We define fuel consumption as

$$fuelcon = 0.4 liter/km \tag{31}$$

and

$$speed = 40 km/h \tag{32}$$

assuming an optimal speed of 32-52 km/h related to efficient fuel consumption (Wang and Rakha 2017) and

$$factor = 2 \tag{33}$$

under the assumption that crudeoil makes up 50% of the diesel price and that changes in crudeoil prices translate to changes in diesel prices. Moreover, we assume a truck carries 20 tonnes (Wang and Rakha 2017):

$$truckload = 20t \tag{34}$$

Lastly, we divide by 60 to get cost per minute to be multiplied with travel time in minutes.

[5] see eia.gov (accessed March 2024) `https://www.eia.gov/tools/faqs/faq.php?id=327&t=9`

6.2.4 Potential revenue

We construct the potential agricultural revenue variable such that it is assumed to have exogenous temporal and spatial variation. Figure 10 and 11 exemplify this for two years in our data.

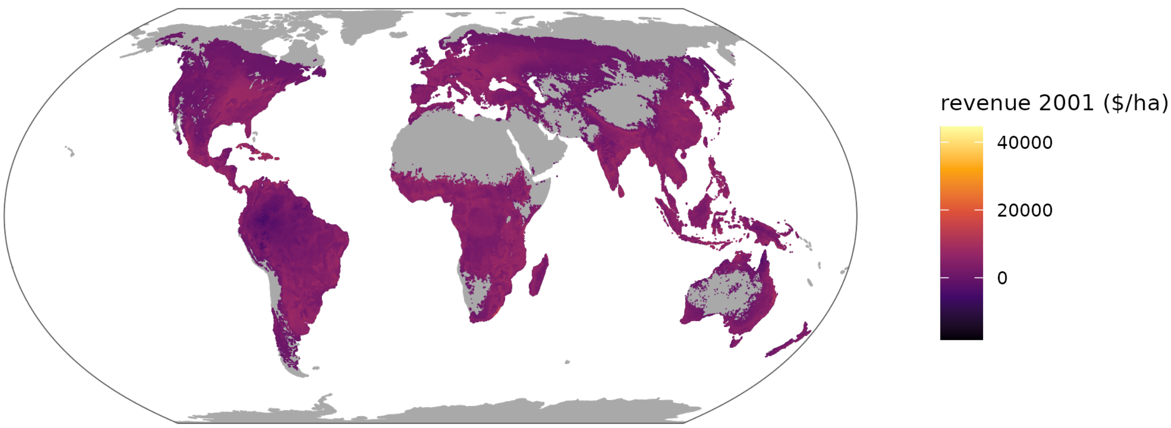

Figure 10: Potential revenue in 2001

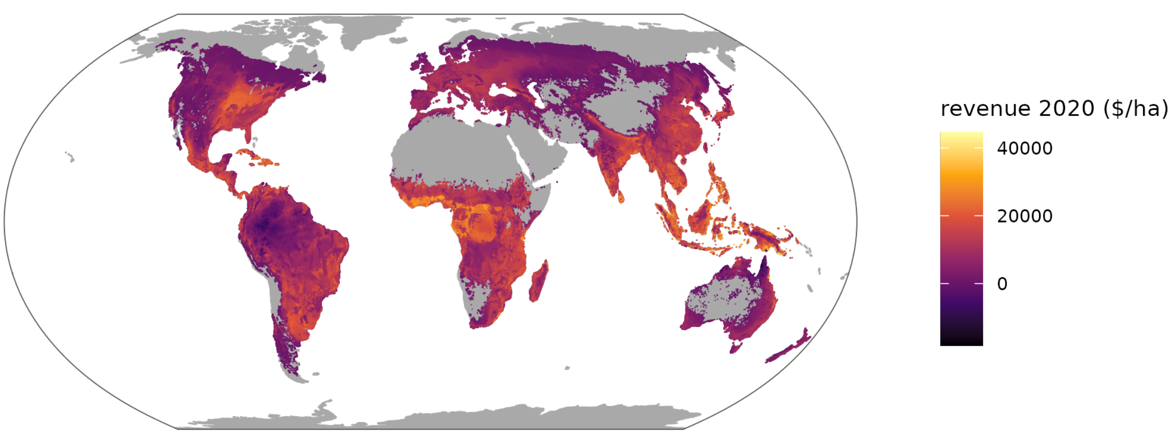

Figure 11: Potential revenue in 2020

6.2.5 Variogram

We explore spatial correlation using a parametric variogram. The exponential form as displayed in figure 12 aligned best with the observed data. After a range of about 100km a plateau for the sill is reached.

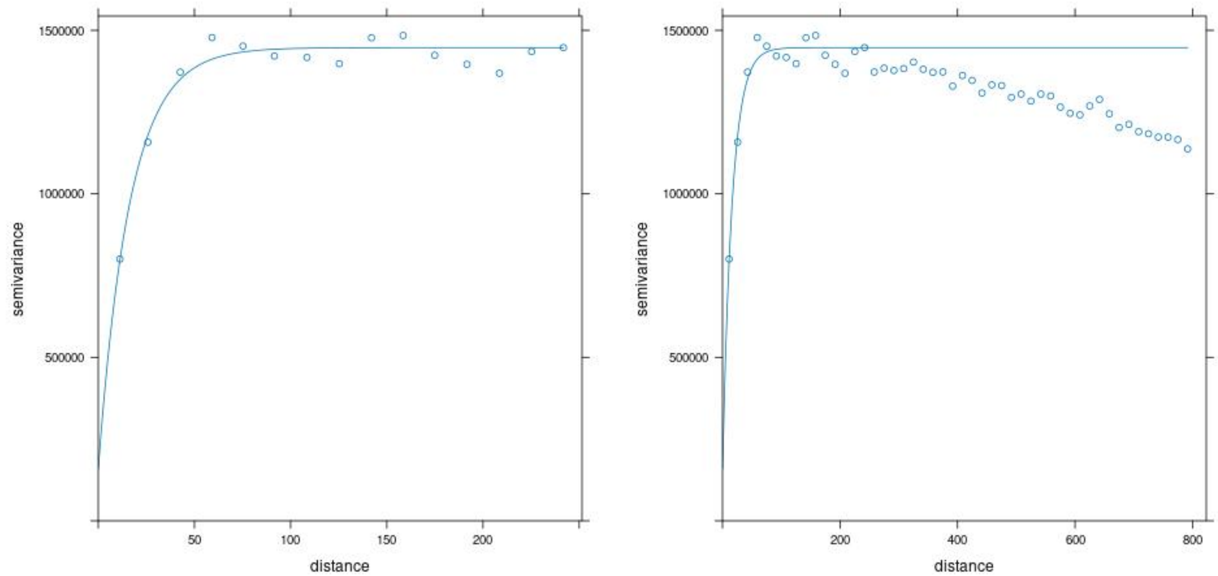

Figure 12: Parametric variograms of exponential form with two different distance cutoffs

6.2.6 Heterogeneity

Since land property rights are presumably important for the decision to invest in agricultural land and to deforest for this purpose, we test the robustness of the average global revenue estimate to the perceived security of property rights. Table 3 first of all shows that the estimates are robust to subsetting the data to observations for which property rights data is available, with a slight increase in the treecover estimate (Model 1 vs Model 2). Model 3 shows that adding an interaction term of revenues and continuous tenure security (normalized to z-scores) results in an insignificant effect of zero. Creating an interaction term in Model 4

Table 3: Estimation results for the global model of deforestation under tenure security

	Model 1	Model 2	Model 3	Model 4	Model 5
revenue	**0.02*****	**0.02*****	**0.02*****		**0.02*****
	(0.00)	(0.00)	(0.01)		(0.01)
treecover	**1.39*****	**1.48*****	**1.48*****	**1.48*****	**1.48*****
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
revenue:security normalized			0.00		
			(0.00)		
revenue:security high				**0.02***	
				(0.01)	
revenue:security low				**0.02*****	
				(0.01)	
revenue:high security dummy					-0.00
					(0.01)
Num. obs.	20337441	18524759	18524759	18524759	18524759
FE: grid cell	1020903	929702	929702	929702	929702
FE: year&country	3080	2380	2380	2380	2380
Deviance	242116.95	227699.99	227698.31	227699.72	227699.72
Log Likelihood					
Pseudo R^2					

Note: Conley standard errors in parentheses. *** indicates significance at the 1% confidence level.

with a categorical indicator for high (above medium) and low (below medium) tenure security, shows similar effects with even stronger significance for places of low tenure security. Lastly, including a dummy with high tenure security = 1 shows that the estimate of the difference between groups is insignificant and 0.

The estimate for a change in potential agricultural revenues is our key parameter of interest, as it is also used in the simulations to account for carbon pricing. When we calculate the average estimate by temperate and tropical regions, we can see that it is robust to the overall average for the main model (see figure 13 a,b). After interacting revenues with a variable indicating whether the grid cell is located in a tropical or temperate region, the coefficient for tropical regions is close to the one from our main model specification (see figure

13 c). For temperate regions the interacted estimate is lower, so that our main specification might overestimate the change in deforestation potentially for these regions. However, for tropical regions, that contribute a substantial share to globally avoided emissions due to carbon pricing, the estimate of the main model is rather close to the one for the tropical interaction term.

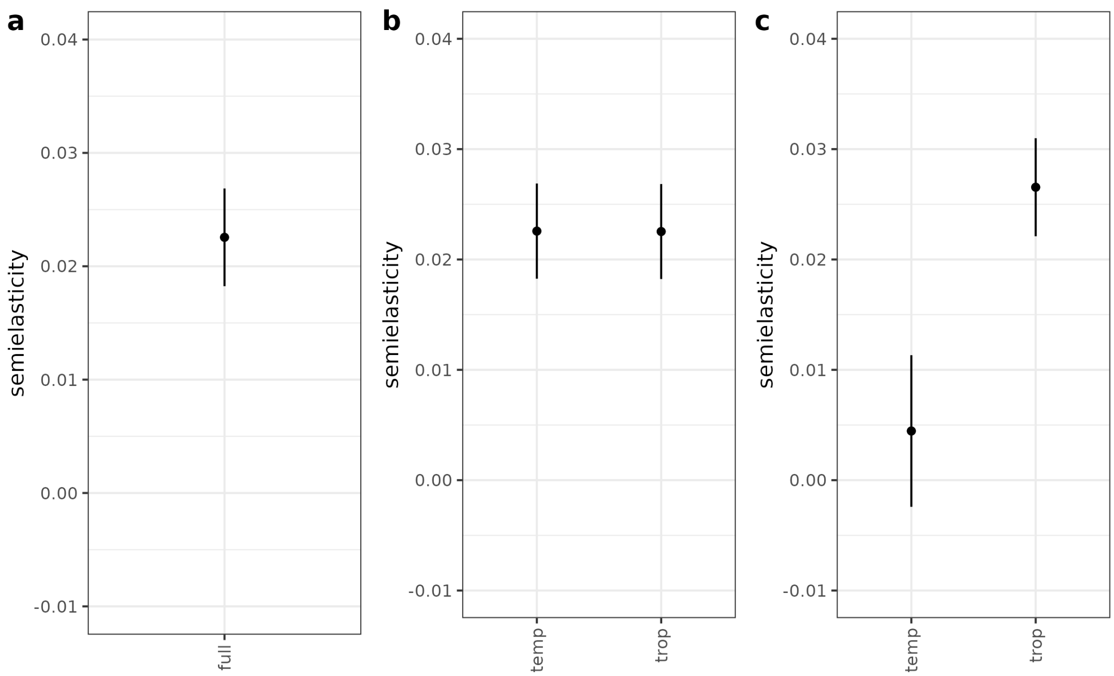

Figure 13: Semi-elasticity estimates, a: main model average, b: main model grouped by temperate and tropical regions, c: adjusted main model for interaction of revenue and temperate vs. tropical region and also grouped by regions

6.3 Implications of endogenous price feedback

For the model simulations presented in the manuscript, we use endogenous prices constructed as explained in section 3.3.2 of the manuscript. For this exercise, 2020 global crop prices are annually adjusted in response to the additional cropland area available after deforestation.

Resulting percentage price changes over time are small and decline with increasing carbon prices as shown in figure 14. This is in line with expectations, since higher carbon prices reduce deforestation and thus the price shock resulting from additionally available cropland. Exogenous global trends and expectations of economic changes are not reflected in these prices.

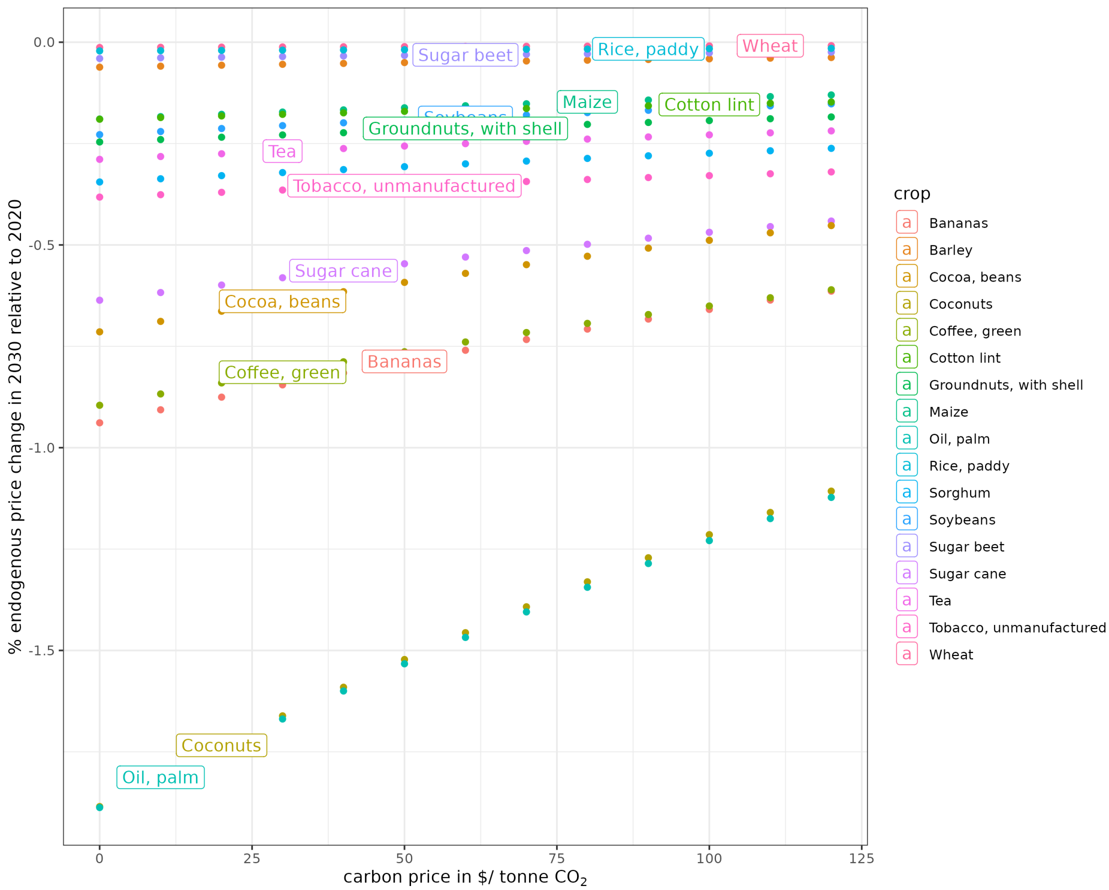

Figure 14: Endogenous crop price changes over time under different carbon prices

In figure 15 we compare the aggregated avoided carbon emissions from reduced deforestation under the endogenous price specification to three alternative price trend assumptions: First, we keep crop revenues fixed at 2020 price levels. Second, we keep crop prices fixed at 2020 price levels but allow for technological progress and changes in transportation costs over time. Third, we use prices reflecting exogenous price trends as provided by OECD and FAO (2022), but that do not account for endogenous effects from deforestation. Globally aggregated avoided emissions are on a very similar order of magnitude under all price assumptions. Only at higher carbon prices a marginal difference becomes apparent. It suggests that without considering endogenous price feedbacks and technological progress, the abatement potential of avoided deforestation will be slightly underestimated. On the other hand, general macroeconomic changes could potentially counteract this development.

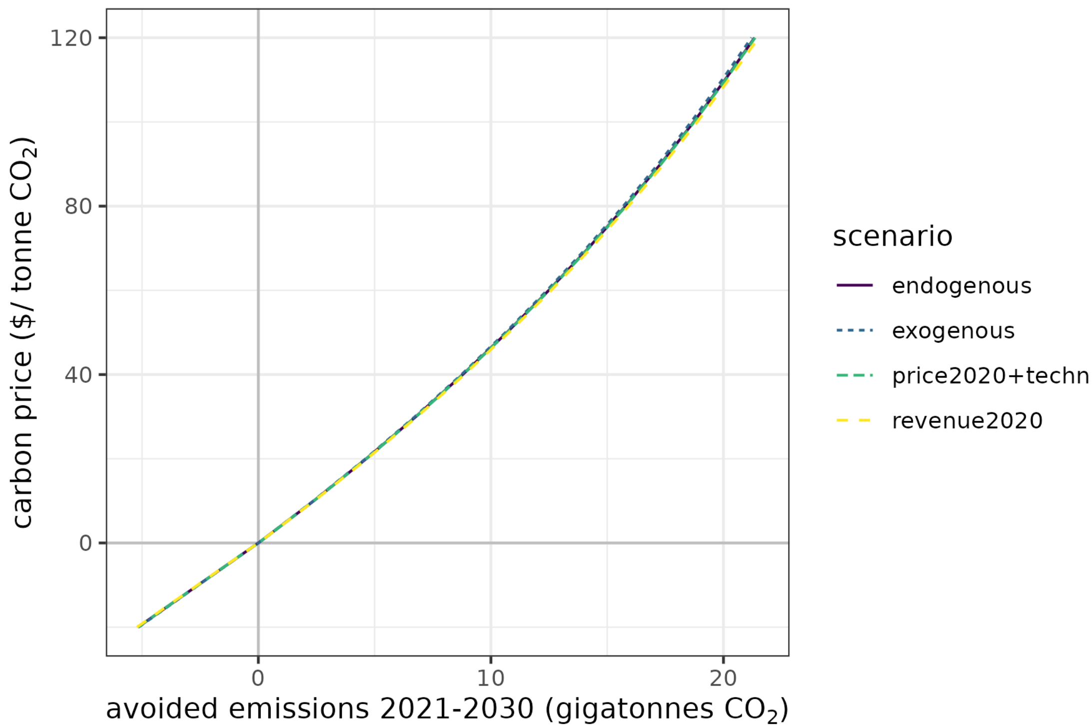

Figure 15: Comparison of additionally avoided emissions for different carbon price trends over 2021-2030 and under full information assuming an endogenous price feedback (main specification), fixed prices at 2020 levels, and exogenous global crop prices.