1 **Supplemental Information Supporting Information Corrected February 16, 2012**

- 2 **Data**
- 3 Forest cover in the year 2000 was estimated by applying a 50% threshold to the Percent Tree Cover Layer
- 4 of the 500 m Moderate Resolution Imaging Spectroradiometer (MODIS)-based Vegetation Continuous
- 5 Fields (VCF) product for the year 2000 (Hansen et al, 2003). The 50% threshold was selected to
- 6 distinguish mature forest from agricultural fallows using high-resolution, Landsat-based forest cover
- 7 maps for parts of Indonesia. This threshold has been applied by similar analyses in other tropical regions
- 8 (Leimgruber et al 2005; Harper et al 2007; Killeen et al 2007).
- 9 Our dependent variable, percent deforestation for the period 2000-2005, was derived by rescaling rates of
- 10 deforestation from data on the distribution of deforestation (tree cover loss estimates from the 463 m
- 11 MODIS VCF product; Hansen et al. 2008) upward by a factor of 2.147 to match data on the total rate of
- 12 deforestation (derived from analysis of a stratified, random sample of 77 18.5km x 18.5km blocks of 28.5

13 m resolution Landsat images; Hansen et al 2008; Hansen et al 2009). An alternative data set on forest

- 14 cover loss (Miettenen, 2011) was explored in a sensitivity analysis (Table SI9).
- 15 Our primary explanatory variable, net present potential gross agricultural revenue, was obtained from
- 16 Naidoo and Iwamura (2007). In this 5' data set the annual potential gross agricultural revenue in 2000
- 17 US\$ was calculated by multiplying the annual yield of the highest-return agricultural commodity in every
- 18 global agro-ecological zone (Fischer *et al*, 2000) by the average market price for that agricultural
- 19 commodity from 1995-2005 [\(http://faostat.fao.org\)](http://faostat.fao.org/). Net present value was obtained by summing annual
- 20 revenue over 30 years and applying a discount rate of 10%, following a different application of the same
- 21 data set in the Stern Review (Grieg-Gran, 2006).
- 22 Because the data on potential agricultural revenue was constructed using coarse global information, we
- 23 examined in detail the robustness of the relationship between the revenue data and deforestation (Table
- 24 SI10). A first-order comparison of increasing increments of \$100/ha/yr potential agricultural revenue and
- 25 five alternative indicators of long-term and short-term deforestation (Hansen 2006; Hansen 2008; Hansen
- 26 2009; Miettenen 2011; Miettenen 2012) shows that the extent of remaining forest cover is nearly
- 27 monotonically decreasing in potential revenue; the short-term deforestation rate and extent of palm
- 28 plantation are both nearly monotonically increasing in potential revenue for all but the highest increments
- 29 of revenue.
- 30 Control variables included average slope and elevation (Jarvis et al, 2008), Euclidean distance from
- 31 nearest national or regional roads and from provincial capitals (NGA, 2000), boundaries for 33 provinces
- 32 and 440 districts from the year 2003, national parks and other protected areas from the year 2006, and

33 logging concessions (HPH), timber concessions (HTI) and estate crop concessions (*kebun*) from the year

- 34 2005 (Minnemeyer et al, 2009). Spatial overlap between protected areas and concessions was negligible,
- 35 with fewer than 1% of cells containing both designations.
- 36 Emissions from deforestation were calculated based on the release of 100% of above- and below-ground
- 37 forest biomass carbon (Gibbs and Brown, 2007) plus 10% of soil carbon content in the top 30cm of non-
- 38 peat soil (FAO 2008). On peat soils, soil emissions were estimated based on the average 30-year non-
- 39 discounted emissions for the agricultural land type (large croplands; small-scale agriculture; shrublands)
- to which such forest are converted, weighted by the area of each of these land types in historical
- conversion across Indonesia (Hoojier, 2010). The resulting estimate of national average soil carbon
- 42 emissions following deforestation on peatlands was 1474 tCO_2 e/ha, which compares to a tropical average
- 43 of 1,486 \pm 183 tCO₂e/ha calculated by Murdiyarso et al (2010). Peat extent was obtained for Sumatra
- (Wahyunto, 2003), Kalimantan (Wahyunto, 2004) and Papua (Wahyunto, 2006), which are considered to
- contain the vast majority of Indonesia's peat soils. Alternative biomass carbon data (WHRC, 2011) and
- peat emission factors were explored in a sensitivity analysis (Table SI9).
- Data were standardized into a single equal-area projection of uniform extent and gridded into 226,348
- 3km x 3km grid cells across all of Indonesia using ArcGIS 9.3.1. This grid cell resolution was chosen to
- comply with size limitations of MS Excel. We removed grid cells for which values were missing from
- the agricultural revenue dataset (n=25,431) or other data sets (n=5,451) leaving 195,466 grid cells
- representing 91.8% of the land area and 95.8% of the forest area of the original data.
-

Comparison of data with other published sources

Observed deforestation in Indonesia from 2000-2005 was 687,000 ha/yr (Figure 1a), producing estimated

55 emissions from deforestation of 860 MtCO₂e/yr, of which an estimated 592 MtCO₂e/yr was from forests

on peat soil. Deforestation compares to estimates that range from 310,000 ha/yr (FAO 2010) to 703,000

- ha/yr (Ministry of Forestry, 2008) to 1.87 million ha/yr (FAO 2005) over the 2000-2005 time period, or
- 58 1.1 million ha/yr in 2005 (DNPI, 2010). Emissions compare to estimates of 502 MtCO₂e/yr from
- 59 deforestation, of which 186 MtCO₂e/yr was associated with peat (Ministry of Forestry, 2008); 1.459
- 60 GtCO₂e/yr over the time period from land use, land use change and forestry (CAIT, 2010); and 1.610
- 61 GtCO₂e/yr emissions in 2005 from land use change, of which 770 MtCO₂e/yr was from peat (DNPI,
- 2010).
-

Econometric methods

We predicted site-level deforestation without carbon payments based on the relationship between the

observed pattern of historical deforestation and spatial variation in sites' geographic and agricultural

characteristics. Our empirical model builds on the theory that land-use decision makers will choose a rate

- of conversion from forest to agriculture that maximizes the present discounted value of a future stream of
- net benefits and costs of conversion. Given this theoretical framework we regressed percent deforestation
- from 2000-2005 on cost and benefit variables for all 166,343 3km x 3km grid cells for which forest cover
- was present in the year 2000 (Eq. 1). We proxied for the gross economic benefit of conversion using
- estimated net present value of potential gross agricultural revenue. We proxied for fixed and variable costs of converting forest to agriculture using a constant term and a linear combination of sites' slope,
- elevation, natural logarithm of the distance to the nearest road, natural logarithm of the distance to the
- nearest provincial capital, and the percent of cell contained within a national park, other protected area,
- logging concession, timber concession, or estate crop concession, following empirical literature on
- determinants of deforestation (e.g. Nelson and Hellerstein, 1995; Laurence et al 2002; Chomitz and
- Thomas 2003; Pfaff et al 2007). In the absence of multi-period data on deforestation and most other
- explanatory variables, we relied on data on changes in forest cover from a single time period. Eventually
- multi-period data sets could be used to isolate changes in deforestation due to changes in agricultural
- returns, infrastructure, or legal designation at particular sites. The combination of explanatory variables
- included in the regression was selected to maximize the district-level correlation between observed and
- predicted deforestation (Table SI7) without directly stratifying by geographic boundaries. The selected
- variables also provided the best combination of parsimony and fit, as determined by the Akaike
- Information Criterion (AIC) (Table SI7).
- Recognizing that the statistical relationship between deforestation and site characteristics may vary across
- a country as large and geographically diverse as Indonesia, we stratified sites into four classes based on
- forest cover, with approximately 42,000 sites in each class (Table SI1). Stratifying based on a larger
- number of forest cover classes did not improve the AIC. Explanatory variables (Table SI2) were
- interacted with these classes in the regression.
- We estimated the influence of explanatory variables on deforestation (Eq. 1) using a Poisson quasi-
- maximum likelihood estimator (QMLE) (Wooldridge, 2002; Burgess et al), which is theoretically
- consistent with 3km x 3km forest cover loss being a count of independent, discrete binary 463m x 463m
- forest cover loss/maintenance observations from the remote sensing data. A Poisson model tolerates zero
- values, and generates a distribution of predicted values which fits the distribution of observed data, which
- is concentrated nearest to zero deforestation and diminishes toward greater levels of deforestation.
- 97 Because the data for percent deforestation is slightly overdispersed (mean=0.067; variance=0.078;
- n=166,343), we considered a negative binomial regression, resulting in outputs that are highly correlated
- with those of the Poisson regression (Table SI5, Table SI7). Standard errors were specified to be robust
- to heteroskedacticity. The inclusion of spatially lagged deforestation as an explanatory variable increased
- overall explanatory power, but had little effect on the significance or magnitude of coefficients on
- observable site characteristics (Table SI7). Alternative functional forms, explanatory variables, and
- stratification classes were explored to confirm robustness (Tables SI3-SI6).
- Explanatory variables used to construct the reference scenario were significantly correlated with observed
- deforestation, producing coefficients with expected signs and plausible magnitudes (Table SI3).
- Consistent with results widely observed elsewhere, deforestation was found to be higher at lower and
- flatter sites, and closer to roads and provincial capitals, controlling for other factors. Deforestation was
- also lower in national parks and other protected areas, and higher in timber and estate crop concessions,
- controlling for other factors. This likely reflects variation in underlying unobservable site characteristics
- associated with the non-random allocation of these land-use designations, in addition to the impact of the
- designations themselves (Pfaff et al, 2009). Deforestation was lower in logging concessions, controlling
- for other factors, possibly reflecting a logging moratorium issued in May 2002, or that forest degradation
- due to selective logging may not have been identified in our deforestation data set.
- Potential gross agricultural revenue was significantly and positively correlated with observed
- deforestation; this relationship was robust to the use of an alternative data set on forest cover loss (Table
- SI6). We examined the impact of potential bias in agricultural revenue data by estimating emission
- reductions and revenue at the high and low extremes of the 95% confidence intervals around the
- coefficient on the effect of potential gross agricultural revenue on deforestation (Table SI9). We
- examined the impact of potential noise in agricultural revenue data by selecting a random draw for each
- site from the confidence interval around the same coefficient (Table SI9).
- We used the econometric model (Eq. 1) to predict deforestation at every site in the absence of REDD+
- (Eq. 2) (the "reference scenario"). This generates an effective land rental value for every site (Eq. 3),
- based not only on potential gross agricultural revenues but also on our proxies fixed and variable land
- conversion costs. We adjusted the econometric model based on hypothetical carbon payments to predict
- deforestation at every site under a REDD+ program (Figure SI1) (Eq. 4,6).

Parameter choices and sensitivities

- We selected a default price of 2008 US\$10/tCO2e for ease of comparison with other studies. Our
- estimates of abatement in response to a \$10/tCO2e carbon price fall within the range of estimates of
- abatement potential from REDD+ in Southeast Asia produced by global forestry and land-use models: 50
- MtCO2e/yr in the Generalized Comprehensive Mitigation Assessment Process Model (GCOMAP); 70
- MtCO2e/yr in the Dynamic Integrated Model of Forestry and Alternative Land Use (DIMA); 875
- MtCO2e/yr in the Global Timber Model (GTM)) [7]; and 233 MtCO2e/yr in a bottom-up model of
- REDD+ in smallholder landscapes and fire prevention in Indonesia [20].
- The effective elasticity parameter was calibrated so that leakage of deforested area matched estimates
- generated by a 35-sector, 5-region general equilibrium model of the Indonesian economy (IRSA-
- Indonesia-5; [50]), in which a 10% exogenous decrease in estate crop production in each one of five
- regions in turn (Java/Bali; Sumatra; Kalimantan; Sulawesi; Eastern Indonesia) produced an average
- increase in production elsewhere within the country of 18% of the initial decrease in production.
- Variations in agricultural prices and the pressure for intranational leakage were explored in a sensitivity
- analysis (Table SI9).
- We tested the sensitivity of estimated impacts to a variety of policy variables (Table SI8) and model
- parameters (Table SI9). Higher carbon prices resulted in greater abatement. We selected 20% revenue
- sharing and 20% responsibility sharing as illustrative values in the improved voluntary incentive
- structure. Greater levels of revenue sharing resulted in less overall abatement but augmented a
- programmatic budget surplus, while greater levels of responsibility sharing resulted in greater
- participation, greater overall abatement, and an augmented programmatic budget surplus. Optimal levels
- of revenue and responsibility sharing would depend on a country's relative preference for program
- effectiveness and equity of distribution of revenues across scales. Scaling sub-national reference levels
- downward uniformly from business-as-usual rates resulted in less participation and less overall abatement
- but augmented a programmatic budget surplus.
-
- In the absence of spatially explicit data, we proxied for potential transaction costs through three
- sensitivity analyses (Table SI9). District-level implementation and monitoring costs diminished net
- reductions and revenue very little, as some small districts opted out but larger districts continued to
- participate in REDD+. On the other hand, site-level costs (e.g. those related to enforcement, management
- or forgone logging revenue) had a stronger dampening effect on emission reductions. Governance and
- institutional barriers, proxied through increases to local decision makers' preference for agricultural
- revenue relative to carbon revenue, also resulted in diminished emission reductions.
-
- The model developed here can potentially be extended to examine a number of interesting topics beyond
- the scope of the current analysis, including a richer suite of land-use changes (e.g. logging and forest
- degradation; reforestation) and policy decisions (e.g. land tenure; infrastructure; agricultural subsidies and
- taxes; conservation of biodiversity and ecosystem services).

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241 **Table SI1 – Forest cover classes**

242

244 **Table SI2 – Summary statistics**

Variable	Forest cover class	Mean	Std. Dev.	Min	Max
Deforestation rate (%/5yr)	None				
	Low	10.1%	36.9%	0%	1251%
	Low-medium	5.5%	21.0%	0%	297%
	Medium-high	3.4%	16.7%	0%	288%
	High	2.4%	13.9%	0%	248%
NPV of potential agricultural revenue	None	\$4,335	\$5,104	\$-	\$187,644
(\$/ha)	Low	\$2,811	\$3,675	\$-	\$187,644
	Low-medium	\$2,173	\$3,880	\$-	\$187,644
	Medium-high	\$1,644	\$2,354	\$-	\$164,483
	High	\$1,304	\$1,386	$$-$	\$91,738
Slope (°)	None	3°	4°	0°	36°
	Low	4°	5°	0°	40°
	Low-medium	7°	7°	0°	40°
	Medium-high	10°	8°	0°	37°
	High	12°	7°	0°	35°
Elevation (m)	None	153	457	0	4496
	Low	177	420	0	4375
	Low-medium	348	585	0	4046
	Medium-high	487	581	0	3794
	High	565	540	$\mathbf 0$	3345
Distance from road (km)	None	37	76	0	606
	Low	39	71	0	603
	Low-medium	67	88	$\pmb{0}$	602
	Medium-high	80	91	0	600
	High	85	96	0	514
Distance from capital (km)	None	164	157	1	816
	Low	183	159	1	790
	Low-medium	238	167	3	778
	Medium-high	260	162	1	755
	High	283	177	3	752
National park (%)	None	3%	16%	0%	100%
	Low	3%	16%	0%	100%
	Low-medium	5%	20%	0%	100%
	Medium-high	8%	26%	0%	100%
	High	13%	33%	0%	100%
Other protected area (%)	None	2%	14%	0%	100%
	Low	3%	16%	0%	100%
	Low-medium	4%	19%	0%	100%
	Medium-high	5%	20%	0%	100%
	High	6%	22%	0%	100%
Logging concession (%)	None	4%	18%	0%	100%
	Low	1%	11%	0%	100%
	Low-medium	4%	18%	0%	100%
	Medium-high	5%	22%	0%	100%
	High	5%	21%	0%	100%
Timber concession (%)	None	3%	17%	0%	100%
	Low	1%	11%	0%	100%
	Low-medium	1%	11%	0%	100%
	Medium-high	1%	8%	0%	100%

 ^{*} Deforestation rate exceeds 100% in some cases because total deforestation rates from MODIS data were scaled based on LANDSAT data. See Data.

246

248 **Table SI3 – Determinants of forest cover loss: Model specifications 1-3.** Robust standard errors;

249 n=166,297. *A coefficient of 0.1 indicates that each unit increase in the driver variable is correlated with*

250 *a 10% increase in the probability of deforestation.*

253 **Table SI4 – Determinants of forest cover loss: Model specifications 4-6.** Robust standard errors;

254 n=166,297. *A coefficient of 0.1 indicates that each unit increase in the driver variable is correlated with* 255 *a 10% increase in the probability of deforestation.*

258 **Table SI5 – Determinants of forest cover loss: Model specifications 7-10.** Robust standard errors;

259 n=166,297. *A coefficient of 0.1 indicates that each unit increase in the driver variable is correlated with* 260 *a 10% increase in the probability of deforestation.*

263 **Table SI6 – Determinants of forest cover loss: Model specifications 10-11.** Robust standard errors;

264 n=166,297. *A coefficient of 0.1 indicates that each unit increase in the driver variable is correlated with* 265 *a 10% increase in the probability of deforestation.*

266 *****The spatial lag regression includes as a regressor the deforestation rate of the cell immediately adjacent

267 to the east, where applicable. n=163,464.

268 **Table SI7 – Model specifications compared.**

270 **Table SI8 – Sensitivity of impacts to key policy variables.** Results are outputs of OSIRIS-Indonesia

271 v1.5 using the following default parameter assumptions: "effective" price elasticity of demand for frontier

272 agriculture=3.8; exogenous agricultural price increase=0%; peat emission factor=1474 tCO₂e/ha; social

273 preference for agricultural revenue=1.0; start-up and transaction costs=\$0.

274 (A) Abatement (MtCO₂e/yr)
275 (N) National government net

 (N) National government net revenue (million $\frac{f}{f}(y)$

276 (D) District revenue from REDD+ less penalties and transaction costs (million \$/yr)
^{*}default policy setting

*default policy setting

278 **Table SI9 – Sensitivity of impacts to variation in key parameters.** Results are outputs of OSIRIS-

279 Indonesia v1.5 using the following default parameter assumptions: carbon price= $$10/tCO₂e$; "effective"

280 price elasticity of demand for frontier agriculture=3.8; exogenous agricultural price increase=0%; peat

281 emission factor=1474 tCO₂e/ha; social preference for agricultural revenue=1.0; start-up and transaction costs=\$0.

 $costs = $0.$

283 (A) Abatement (MtCO₂e/yr)
284 (N) National government net

284 (N) National government net revenue (million \$/yr)
285 (D) District revenue from REDD+ less penalties and

(D) District revenue from REDD+ less penalties and transaction costs (million $\frac{f}{f}$ yr)

²⁸⁶ *default parameter value
287 ¹ Effectiveness of improved incentives is calculated as the difference in abatement between the basic and improved

288 voluntary incentives structures divided by the difference in abatement between the basic voluntary incentive 289 structure and the mandatory incentive structure

289 structure and the mandatory incentive structure
 $290 \frac{2}$ Low/random draw/high=lower end of/random

²Low/random draw/high=lower end of/random draw from/higher end of 95% confidence interval around the econometrically estimated effect of revenue on deforestation (see Econometric Methods)

292 ³ Range of peat emission factors based on "low," "likely" and "high" estimates from Hoojier et al (2010).

- 294 **Table SI10: First-order relationship between potential agricultural revenue and alternative**
- 295 **indicators of short-term and long-term deforestation**

Net potential agricultural revenue at site minus net potential carbon revenue at site (\$/ha)

 Figure SI1 – Predicted site-level deforestation as a function of potential agricultural and carbon

revenue. Many previous studies have estimated the abatement potential of REDD+ policies based on the

deterministic assumption that deforestation could be avoided entirely if and only if revenue from carbon

payments exceeds income from alternative land uses ("opportunity cost approach"). We estimate the

marginal impact of potential carbon payments on site-level deforestation by using a Poisson regression to

determine the empirical relationship between the pattern of observed historical deforestation and spatial

 variation in the benefits and costs of converting forested land to agriculture ("revealed preference approach").

Figure SI2 – District-level allocation of land between forest and agriculture. Based on Figure 2 in

Busch et al 2009. Line *a* represents the district-level supply curve for emissions-producing agricultural

expansion into forest in the absence of a REDD+ mechanism. Greater potential agricultural revenue per

hectare produces greater emissions from deforestation. Line *b* represents the district supply curve if the

 district opts into REDD+ by reducing its emissions below its reference level. This supply curve is shifted inward by the carbon payment, which is a function of the carbon price and the revenue sharing

arrangement. Line *c* is the district supply curve is the district opts out of REDD+ by increasing its

emissions above its reference level. This supply curve is shifted inward by the penalty, which is a

function of the carbon price and the responsibility sharing arrangement. The district chooses the quantity

of emissions from agricultural expansion *m* or *n* which provides greater total carbon revenue and

agricultural revenue at the equilibrium agricultural price.

322 **Figure SI3 – Observed deforestation and predicted deforestation compared for forested districts of**

323 **Indonesia, 2000-2005. (n=401; R=0.68)** Predicted deforestation using model specification 1 (Poisson; 324 stratified by forest cover). Heavy dotted 45[°] line indicates predicted deforestation equal to observed

325 deforestation within a district. Light dotted lines indicate the boundaries within which predicted

326 deforestation is within a factor of ten of observed deforestation.

Equations

Eq. 1 – Predicted deforestation at sites in the absence of REDD+ based on observable site characteristics

$$
y_i = \exp\left(\beta_{k0} + X_i'\beta_{k1} + \beta_{k2}A_i + \epsilon\right)
$$

Here $y_i = (F_i^o - F_i)/F_i^o$ is percent deforestation at site *i*, where F_i^o is forest cover at site *i* at the start of

332 the 2000-2005 observation period, and F'_i is forest cover at site *i* at the end of the observation period.

333 *k* ∈ 1: 4 are classes of observations stratified by initial forest cover (Table SI1). *X_i* is a matrix of observable site characteristics, including slope, elevation, natural logarithm of the distance to the nearest

road, natural logarithm of the distance to the nearest provincial capital, and the percent of site within a

national park, other protected area, logging concession (HPH), timber concession (HTI), or estate crop

concession ($kebun$). A_i is the net present value of gross agricultural revenue potential per hectare at site *i*.

338 The term β_{k0} captures unobserved constant components of the expected net benefits of deforestation.

Eq. 2 – Expected deforestation at sites in the absence of REDD+

$$
\hat{y}_{i-without\, REDD+} = \exp\left(\hat{\beta}_{k0} + X_i'\hat{\beta}_{k1} + \hat{\beta}_{k2}A_i\right)
$$

Here $\hat{y}_{i-without REDD+}$ is the expected deforestation at site *i* in the absence of REDD+. The distribution 342 across the country of all $\hat{y}_{i-without REDD+}$ is the reference scenario.

Eq. 3 – Effective land rental value at a site

$$
A_i + \frac{\hat{\beta}_{k0} + X_i'\hat{\beta}_{k1}}{\hat{\beta}_{k2}}
$$

Effective land rental value at a site includes not only potential gross agricultural revenue but also costs.

Eq. 4 – Expected deforestation at a site in a district that opts in to REDD+

$$
\hat{y}_{i-with\, REDD +;\, opt\, in} = \exp\left(\hat{\beta}_{k0} + X_i'\hat{\beta}_{k1} + \hat{\beta}_{k2}((1 + \tau_1 + \tau_2)A_i - R_i)\right)
$$

348 Here τ_1 is the endogenous increase in price due to intranational leakage, and τ_2 is the exogenous increase
349 in price due to international leakage. R_i is the marginal carbon revenue per hectare of forest a in price due to international leakage. R_i is the marginal carbon revenue per hectare of forest accruing to a district that has opted in to REDD+.

Eq. 5 – Carbon revenue per hectare of forest accruing to a district which has opted in to REDD+

$$
R_i = p_C * (1 - r) * E_i
$$

Here p_c is the price paid by international buyers for carbon emission reductions, $r \in [0,1]$ is the portion of world carbon price withheld by the national government under a revenue sharing arrangement (e.g. $r=$

- 354 of world carbon price withheld by the national government under a revenue sharing arrangement (e.g. *r*=0
- 355 world signify that carbon price accrues entirely to the district), and E_i is the emission reductions resulting from a decrease in deforestation at parcel *i* (tCO₂e/ha).

from a decrease in deforestation at parcel i (tCO₂e/ha).

357

358 Eq. 6 – Expected deforestation at a site in a district that opts in to REDD+

$$
\hat{y}_{i-with\ REDD+; \ opt \ out} = \exp (\hat{\beta}_{k0} + X_i'\hat{\beta}_{k1} + \hat{\beta}_{k2}((1 + \tau_1 + \tau_2)A_i - C_i))
$$

 359 Here C_i is the marginal cost per hectare of deforestation incurred by a district which has opted out of 360 REDD+.

361

362 Eq. 7 – Cost per hectare of deforestation incurred by a district which has opted out of REDD+

$$
C_i = p_C * (1 - l) * E_i
$$

363 Here $l \in [0,1]$ is the share of cost for emission increases borne by the national government under a 364 responsibility-sharing arrangement (e.g. *l*=1 would signify that cost is borne entirely by the national 365 government).

366

367 Eq. 8 – Districts' participation decision

368
$$
p_c*(1-r)[RL_j-\sum_{i\in j}(\hat{y}_{i-with\,REDD+j\,opt\,in}*F_i^o*E_i)] >
$$

369 $\gamma[\sum_{i \in j} (\hat{y}_{i}-with\text{ REDD}+; \text{ opt out } -\hat{y}_{i}-with\text{ REDD}+; \text{ opt in}) * F_i^o * (1+\tau_1+\tau_2) * A_i]$

$$
-p_c*(1-l)*\sum_{i\in j}(\hat{y}_{i-with\ REDD+j\ opt\ out}*F_i^o*E_i-RL_j)
$$

370 Here RL_j is the reference level for district *j*, and F_i^o is the starting forest cover at site *i*. Parameter γ 371 represents the district's preference for agricultural revenue relative to carbon revenue.

372

373 Eq. 9 – Expected aggregate deforestation within a district, without REDD+

$$
D_{j,without\ REDD+} = \sum_{i \in j} (\hat{y}_{i-without\ REDD+} * F_i^o)
$$

Eq. 10 – Expected aggregate deforestation within a district, with REDD+

$$
D_{j, with\, REDD+} = \sum_{i \in j} (\hat{y}_{i-with\, REDD+} * F_i^o)
$$

377 Eq. 11 – Expected aggregate emissions within a district, without REDD+
$$
\overline{a}
$$

$$
E_{j, without\ REDD+} = \sum_{i \in j} (\hat{y}_{i-without\ REDD+} * F_i^o * E_i)
$$

Eq. 12 – Expected aggregate emissions within a district, with REDD+
\n380
$$
E_{j, with REDD+} = \sum_{i \in j} (\hat{y}_{i-with REDD+} * F_i^o * E_i).
$$

\n381
\n382
\n383 Eq. 13 – Expected carbon revenue accruing to district from opting in to REDD+
\n384 $B_j = \max \{0, (RL_j - E_{j, with REDD+}) * p_c * (1 - r)\}.$
\n385
\n386
\n387 Eq. 14 – Expected cost incurred by a district from opting out of REDD+
\n $C_j = \max \{0, (E_{j, without REDD+} - RL_j) * p_c * (1 - l)\}$
\n388
\n389
\n390 Eq. 15 – Expected aggregate deforestation nationwide, without REDD+
\n $D_{without REDD+} = \sum_j D_{j, without REDD+}$

Eq. 16 – Expected aggregate deforestation nationwide, with REDD+

$$
D_{\text{with REDD+}} = \sum_{j} D_{j,\text{with REDD+}}
$$

 Eq. 17 – Endogenous increase in potential agricultural revenue due to decreased aggregate deforestation nationwide

$$
\tau_1 = \left(\frac{D_{without\ REDD+}}{D_{with\ REDD+}}\right)^e
$$

The "effective elasticity" parameter *e* is functionally equivalent to the price elasticity of demand for

frontier agriculture, but is calibrated to also incorporate economy-wide feedbacks in the domestic labor

and productive capital markets from the separate IRSA-5 general equilibrium model of the Indonesian

economy.