Supplementary Material of the paper
(not for publication)

"Title: What has driven deforestation in developing countries since the 2000s? Evidence from new remote-sensing data

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A list of diagnosis and robustness checks is documented in this appendix.

A. Serial correlation and Heteroscedasticity issues

The Fixed Effect regression model usually computed with panel data set assumes that the disturbances are homoscedastic with the same variance across time and individuals. To test heteroscedasticity issues, we use the Modified Wald test for group-wise heteroscedasticity in fixed effect regression model residuals. The null hypothesis specifies that $\sigma_i^2 = \sigma^2 \; for \; i = 1, \ldots, N$ where N is the number of Cross sectional units (countries here). The test is distributed as a Chi Square under the null of homoscedasticity. The result of the Wald test applied to the FE regression model of the table 3 (similar to the model used in column 1 without standard errors clustering) leads to reject the null hypothesis of homoscedasticity in the residuals of our FE regression model and show that this issue must be taken into account in our estimates.

H0: $\sigma (i)^2 = \sigma^2$ for all i:
chi2 (121) = 1.9e+05
Prob>chi2 = 0.0000

The presence of group-wise heteroscedasticity is not surprising since different variances in different samples (deforesting countries in our case) could lead to heteroscedasticity and serial correlation issues.

We thus compute estimates using standard errors clustering to obtain valid inference for the usual Fixed Effect estimator (see tables 3 to 5 in the Manuscript). Indeed, using standard errors clustering, standard errors are robust to clustering that is to potential within-cluster correlations. For instance model errors for different time periods for a given country may be correlated, while model errors for different countries are assumed to be uncorrelated. Failure to control for within-cluster errors correlation can lead to misleading narrow confidence intervals, large t-statistics and low p-values.

We used a bootstrap method (non parametric approach for evaluating the distribution of a statistic, based on random re-sampling), which tests for the normality of residuals, with a variance that is increased by simulation (very close to the Monte Carlo method for generating larger samples and more robust variance for a given distribution). Other re-sampling methods, such as jackknife, may be used, but the bootstrap estimate of model prediction bias is more precise than jackknife estimates with linear models such as multiple regression.

Overall, the inference is robust to serial correlation and heteroskedasticity of unknown form. Results using clustering are reported in the paper in tables 3 to 5. Note in addition that serial correlations and heteroscedasticity issues are neglectable when we use a panel with large N and small T as in our case.

Finally, we also test serial correlation that could biases the standard errors using the Wooldridge test (2002) implemented by David Drukker under Stata Software. Based on the

FE regression model of table 2 of the paper, column 1, we find evidence that autocorrelation issues are rejected since the null of no first order autocorrelation cannot be rejected at usual confidence thresholds.

Wooldridge test for autocorrelation in panel data, H0: no first order autocorrelation:

F(1, 118) = 1.516
Prob > F = 0.2207

For robustness checks, we also computed Driscoll and Kraay (1998) estimator, in Table 1, based on a nonparametric covariance matrix estimator leading to heteroscedasticity consistent standard errors robust to different forms of temporal and country/spatial dependence. The results obtained with Driscoll-Kraay standard errors, including 4 lags of the dependant variable, are very similar to the results from the table 2 of our article using standards errors clustering.

Table 1: Driscoll-Kraay standard erros

Regression with Driscoll-Kraay standard errors		Number	of obs	=		1150	
Method: Fixed-effects regression		Number	of groups	=		118	
Group variable (i): code_country		F(9,	9)	=		18545,34	
maximum lag: 4		Prob >	F	=		0	
		within	R-squared	=		0,1086	
		Drisc/Kraay					
dfrst (stand.)	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**	
GDP per capita, WPT (log, 2005 constt, -1) (standardized)	0,8263787	0,1047447	7,89	0	0,5894297	1,063328	
GDP pc growth (2005 constt) (standardized)	0,0305868	0,0097437	3,14	0,012	0,0085449	0,0526286	
Population density (log) (standardized)	1,314519	0,3472077	3,79	0,004	0,5290809	2,099957	
Agricultural land (% country area, -1) (standardized)	0,0355032	0,0793008	0,45	0,665	-0,1438877	0,2148941	
Openness at 2005 constant prices (\%, -1) (standardized)	0,1204355	0,0266905	4,51	0,001	0,0600573	0,1808136	
Terms of trade (standardized)	-0,1068865	0,0186983	-5,72	0	-0,1491851	-0,0645879	
Crop production index (2004-2006 = 100, -1) (standardized)	0,0489579	0,0129047	3,79	0,004	0,0197655	0,0781503	
PolityII (standardized)	-0,0029091	0,0151374	-0,19	0,852	-0,0371524	0,0313341	
Durable (standardized)	0,0151867	0,0188629	0,81	0,442	-0,0274842	0,0578575	
_cons	0,2255345	0,0278517	8,1	0	0,1625296	0,2885394	

B. <u>Multicolinearity issues</u>

In this subsection, we deal with potential collinearity issues and the risk for artefactual explanation of variations of the dependent variable in estimations using interaction terms. By definition, interaction model requires collinearity among explanatory variables. We focus on the collinearity among variables "Agricultural exports (value) per km2 (log, -1) (standardized)" and "Agricultural land (-1) x Agricultural exports (log, -1)")

Althauser (1971) shows that the main terms and the interaction terms are correlated. These correlations are affected in part by the size and the difference in the sample means of both (interaction) variables. Smith and Sasaki (1979) also argue that the inclusion of the interaction term might cause a multicollinearity problem. According to Balli and Sorensen (2013), collinearity is not a problem for regressions with interaction effects of a different nature than elsewhere in empirical economics; if one expects too much from a small sample, correlations between regressors make for fragile inference.

To check collinearity issues, we compute the Variance Inflation Factors (VIF). Based on the model 2 in the manuscript, we thus show that the VIF computations lead to the following results.

- first, it seems that the (potentially artefactual) variance of the dependent variables explained is limited by such collinearity according to the variation inflation factor criterium (average vif: 2.46). We indeed find that the variance inflation factor (VIF) is always lower than 10 (a usual ad-hoc upper bound in econometric studies), indicating moderate collinearity among explanatory variables (although it is relatively high for interaction and interacted variables).

Table 2: VIF results

Variables of model	**VIF**	**1/VIF**
Agricultural exports km2 x Agricultural land	6.97	0.143512
Agricultural exports (value) per km2 (log, -1) (standardized)	5.15	0.194281
Agricultural land (% country area, -1) (standardized)	3.29	0.304000
Population density (log) (standardized)	1.91	0.522544
GDP per capita, WPT (log, 2005 constt, -1) (standardized)	1.31	0.764656
Openness at 2005 constant prices (%, -1) (standardized)	1.30	0.769774
Terms of trade (standardized)	1.28	0.781977
Forests exports (value) per km2 (log, -1) (standardized)	1.22	0.820911
Crop production index (2004-2006 = 100, -1) (standardized)	1.13	0.886870
GDP pc growth (2005 constt) (standardized)	1.04	0.958278
Mean VIF	**2.46**	

- second, coefficients found are relatively stable and the r-squared does not increase significantly across regressions, showing the limited impact of new interaction variables on the explained variance of the explained variable. See the following table (Table 4 in the paper):

Table 4: Drivers of 2001-2010 deforestation, OLS, FE in Low-Income Countries

	(1) dfrst (stand.)	(2) dfrst (stand.)	(3) dfrst (stand.)	(4) dfrst (stand.)	(5) dfrst (stand.)
GDP per capita, WPT (log, 2005 constt, -1) (standardized)	1.082***	1.072***	0.974***	1.533***	0.947***
	(0.230)	(0.213)	(0.247)	(0.303)	(0.270)
GDP pc growth (2005 constt) (standardized)	0.0308*	0.0307*	0.0307*	0.0282	0.0364**
	(0.0160)	(0.0165)	(0.0161)	(0.0239)	(0.0181)
Population density (log) (standardized)	1.690***	1.705***	1.758***	1.666**	1.330***
	(0.494)	(0.511)	(0.474)	(0.633)	(0.427)
Openness at 2005 constant prices (%, -1) (standardized)	0.0889	0.0893	0.0884	0.113	0.110*
	(0.0590)	(0.0573)	(0.0575)	(0.0961)	(0.0646)
Terms of trade (standardized)	−0.108***	−0.113***	−0.118***	−0.123***	−0.0919***
	(0.0292)	(0.0303)	(0.0310)	(0.0386)	(0.0285)
Crop production index (2004-2006 = 100, -1) (standardized)	0.0721*	0.0775**	0.0630*	0.0666	0.0628*
	(0.0369)	(0.0366)	(0.0372)	(0.0572)	(0.0368)
Agricultural land (% country area, -1) (standardized)	0.0895	−0.229		−0.0949	0.153
	(0.225)	(0.218)		(0.374)	(0.197)
Agricultural exports (value) per km2 (log, -1) (standardized)	0.231**	0.709***	0.253**	0.306**	0.240**
	(0.110)	(0.244)	(0.114)	(0.118)	(0.113)
Forestry exports value per km2 (log, -1) (standardized)	−0.0991	−0.0928	−0.105	−0.124	
	(0.0694)	(0.0671)	(0.0703)	(0.0820)	
Agricultural land (-1) × Agricultural exports (log, -1) (stand.)		−0.618***			
		(0.225)			
Forest land cover (log, -1) (standardized)			−0.796		
			(1.226)		
Forest land cover (log, -1) × Agricultural exports (log, -1) (stand.)			0.199**		
			(0.0819)		
Agric. exports value (log, -1) × phase 2 of forest transition (stand.)				0.546*	
				(0.320)	
Agric. exports value (log, -1) × phase 3 of forest transition (stand.)				−0.479***	
				(0.161)	
Agric. exports value (log, -1) × phase 4 of forest transition (stand.)				0.00663	
				(0.141)	
PolityII (standardized)					0.0278
					(0.0631)
Agricultural exports × PolityII					0.114
					(0.0757)
Constant	0.653***	0.684***	0.639***	1.140***	0.544***
	(0.107)	(0.104)	(0.130)	(0.160)	(0.130)
Observations	1136	1136	1136	790	1130
R^2	0.120	0.132	0.131	0.168	0.121
Adjusted R^2	0.113	0.124	0.123	0.155	0.113

Standard errors in parentheses, robust to country clustering
$^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

C. Forest cover proxy

Regarding the remaining issue of the limited quality proxy that we use for forest endowments (agricultural land), we have now backed up our results by showing the same regressions with the forest cover in t-1 (now collinear with the endogenous variable). We thus introduced an additional variable: the forest cover in year t-1 (km2, lagged). We then ran the same regression and found similar results (additional regression shown in column 3 of Table 4 of the paper).

D. Dynamic Panel estimation models

In the paper, we focus on usual panel regression methods such as fixed effects regressions since all diagnostics tests are in favor of this methodology.

In this Appendix, we check the robustness of the fixed effect model by performing a dynamic panel estimation using GMM estimator. Under GMM, our static panel model turns out to be a dynamic panel data model variables and leads to the rejection of the fundamental hypothesis of strict exogeneity of the covariates. As a consequence, the usual estimator computed in the previous static model (estimation by LSDV) is no longer consistent when *N* tends to infinity with fixed *T* (the so-called dynamic panel bias, see Nickell, 1981).

Though an IV estimator is a way to estimate this kind of model, Arellano and al. (1991) have shown that the GMM estimator is the most suitable since it uses more information from the model. From a technical point of view, the GMM approach is based on the first difference of the model ($y_{i,t}$-$y_{i,t-1}$) to remove the fixed effects C_i; the parameters of the models are computed using the moments (theoretical and empirical) of the model (see for instance Greene, 2011, 7th). The main advantage of the GMM is that we do not need to impose a strong hypothesis such as strong exogeneity before the estimation, as in the OLS and Maximum Likelihood cases. It thus produces robust and efficient estimates of our dynamic model of the deforestation rate. However, we show that this dynamic estimation is not needed since lags of the dependent variable do not significantly influence the current deforestation rate, as shown in Table 2 of the paper, unit root is negligible and not significantly different from 0.

Table 2: Drivers of 2001-2010 deforestation, OLS, FE in Low-Income Countries: specification robustness

	(1) (OLS, FE) dfrst (standardized)	(2) (OLS, RE) dfrst (stand.)	(3) (GMM) Annual deforestation (log km2)	(4) (OLS, FE) dfrst (stand.)
L.Annual deforestation (log km2)			−0.0509	
			(0.0842)	
GDP per capita, (log, 2005 constt, -1) (standardized)	0.826***	0.294***		−0.982
	(0.207)	(0.0895)		(1.390)
squared GDP per capita, WPT (log, 2005 constt, -1) (standardized)				1.733
				(1.334)
GDP pc growth (2005 constt) (standardized)	0.0306*	0.0191		0.0354**
	(0.0181)	(0.0190)		(0.0165)
Population density (log) (standardized)	1.315***	0.224***		1.417***
	(0.472)	(0.0763)		(0.502)
Agricultural land (% country area, -1) (standardized)	0.0355	−0.180**		0.0974
	(0.218)	(0.0750)		(0.209)
Openness at 2005 constant prices (%, -1) (standardized)	0.120*	0.214***		0.124*
	(0.0682)	(0.0734)		(0.0648)
Terms of trade (standardized)	−0.107***	−0.0569**		−0.112***
	(0.0318)	(0.0258)		(0.0317)
Crop production index (2004-2006 = 100, -1) (standardized)	0.0490	0.110***		0.0566*
	(0.0360)	(0.0404)		(0.0332)
polityII (standardized)	−0.00291	0.0516		−0.00428
	(0.0380)	(0.0388)		(0.0368)
durable (standardized)	0.0152	0.0307		0.0133
	(0.0647)	(0.0591)		(0.0650)
GDP pc growth (2005 constt)			0.00511	
			(0.00506)	
GDP per capita, (log, 2005 constt, -1)			1.246***	
			(0.352)	
Population density (log)			0.668	
			(0.889)	
Openness at 2005 constant prices (%, -1)			−0.000357	
			(0.00168)	
Agricultural land (% country area, -1)			0.0170	
			(0.0167)	
Terms of trade			−0.00231	
			(0.00183)	
Crop production index (2004-2006 = 100, -1)			0.000328	
			(0.00223)	
PolityII			0.00139	
			(0.0136)	
Durable			0.0182*	
			(0.0107)	
Constant	0.226***	0.136	−4.758	0.226***
	(0.0462)	(0.0997)	(4.250)	(0.0454)
Observations	1150	1150	896	1150
R^2	0.109			0.111
Adjusted R^2	0.102			0.104
between	0.0.433	0.1541		0.0361
within	0.1086	0.0879		0.1114
overall	0.0433	0.1494		0.0373
AB p-value of AR(2)			0.6799	
P-value of Sargan test			0.0000	
P-value of Wald test			0.0000	

Standard errors in parentheses, robust to country clustering

* $p < .1$, ** $p < .05$, *** $p < .01$

E. Non-stationarity issues

To check non-stationarity issues, we perform usual panel unit root tests to investigate the dynamics of our series. First, we test for the presence of a unit root in our series. Panel unit root tests proposed by Levin, Lin and Chu (2002), Im, Pesaran and Shin (2003) and the Fishertype ADF test (Maddala and Wu, 1999) are the most used tests in panel studies. The literature has shown that Maddala and Wu (1999) exhibit the best properties.

However, the so-called *first generation* unit root tests (they assume cross sectional independence) are shown to be inconsistent in the presence of cross sectional dependence, because they suffer from severe size distortions (O'Connel (1998), Philips and Sul (2003), Banerjee et al. (2005)). In this case, the drivers of the deforesting countries are likely to be pair-wise correlated. We thus reinvestigate the unit root testing taking into account common factors using so-called second generation PURT from Pesaran (2007) named CIPS.

Finally, since usual tests are not well suitable to panel datasets with a large number of panel countries and relatively few time periods (here, we have 128 countries and 12 time periods), we use the Harris-Tzavalis (1999) test.

We find clear-cut evidence in favor of the alternative hypothesis that the deforestation rate is stationary. For comparison purposes, we also test population density and openness. The overall results show that cointegration and dynamic panel estimators are not required to estimate the drivers of deforestation considering our panel data set since all main variables are stationary.

Table 3: Panel Unit Root tests for main variables

PURT	**Deforestation rate**	**Openess**	**Population Density**
Levin Lin Chu	-7.2924 (0.0000)	-69.1457 (0.0000)	-18.4251 (0.0000)
Im Pesaran Shin	na	-2.9565 (0.0016)	-0.1900 (0.4247)
Fisher-Maddala (ADF)	1022.467 (0.000)	na	na
Specification	Constant	Constant	Constant
CIPS Pesaran (Second generation) 1 to 4 lags included	-15.055 (0.000) -4.359 (0.000) 0.463 (0.678) 44.840 (1.000)	na	na
Harris Tzavalis	-27.2306 (0.0000)	-3.2129 (0.0007)	10.3825 (1.0000)

Note: AIC selection is used to perform first panel generation tests. Na denotes unavailable results due to computational problems (insufficient number of observations or time dimension). P values are in parenthesis.

F. Test Hausman fixed versus Random effect model

Since non stationarity issues are not present in our panel data set, fixed effects and Random Effects estimator could be used. However, we need to choose between those two estimators and thus we performed the Hausman Fixed versus Random effect test. If the p-value for the Hausman test, where you compare random to fixed-effects is inferior to .05 then the random-effects estimator is not consistent. The fixed-effects estimator is consistent; however, the random-effects estimator is more efficient. The statistic, denoted *m*, is distributed as a Chi2 under the null hypothesis with degrees of freedom corresponding to the dimension of b (parameters). Null hypothesis is that the first estimator is efficient but inconsistent under the alternative while the second estimator is consistent under both hypotheses. Our results (see below) are in favor of the FE estimator.

Table 4: Hausman test

	---- Coefficients ----			
	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
GDP per capita, WPT (log, 2005 constt, -1) (standardized)	1.082204	.6348849	.4473189	.1370821
GDP pc growth (2005 constt) (standardized)	.0308029	.0254869	.0053161	.0031426
Population density (log) (standardized)	1.689799	.0494463	1.640352	.4648295
Openness at 2005 constant prices (\%, -1) (standardized)	.0889401	.1652672	-.076327	.0257418
Terms of trade (standardized)	-.1078828	-.0654791	-.0424037	.0113007
Agricultural land (\% country area, -1) (standardized)	.08953	-.1023128	.1918428	.1939351
Crop production index (2004-2006 = 100, -1) (standardized)	.0721343	.1133331	-.0411988	.0110425
Agricultural exports (value) per km2 (log, -1) (standardized)	.2310043	.2761423	-.045138	.0549796
Forest land cover (log, -1) (standardized)	-.0990735	-.0803701	-.0187035	.0493948

	b = consistent under Ho and Ha; obtained from xtreg
B =	inconsistent under Ha, efficient under Ho; obtained from xt
Test: Ho:	difference in coefficients not systematic
	chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B)
	31.7
	Prob>chi2 = 0.0002
	(V_b-V_B is not positive definite)

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