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On the economic factors of deforestation: what can we learn from quantile analysis?

Olivier Damette[1] and Philippe Delacote[2]

The factors of deforestation at a global level have been widely studied in the empirical economic literature. However, the high heterogeneity among countries considerably limits the overall significance of the results. Using quantile approach, we show that some major deforestation factors are more prevalent in high deforestation countries, giving the insight that those factors have been under-estimated in previous studies.

Keywords: Quantile analysis, Deforestation, Economic development, Environmental Kuznets Curve

1. Université Paris-Est Créteil, France

2. Researcher at INRA - Laboratoire d'Economie Forestière, Nancy, France

Climate Economics Chair
Paris-Dauphine University
CDC Climat

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Abstract

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1 Introduction

Deforestation is a major environmental issue, contributing to climate change, biodiversity losses and soil erosion. About 13 million hectares of forest disappear every year (FAO (2010)). The deforestation drivers have been widely studied over the past years, leading to an ever growing number of empirical multi-country papers. Most papers use cross-section and panel national data to estimate which global factors affect deforestation. Recent work focusing on country-level studies has shown that higher corruption and lower institutional quality (Nguyen-Van and Azomahou (2007)), higher real exchange rate (Arcand et al. (2008)), higher timber harvesting (Damette and Delacote (2011)) or development (Culas (2007), Ewers (2006), Rudel et al. (2005)) can indirectly increase deforestation. Combes-Motel et al. (2009) distinguish structural and policy-related deforestation factors. Nevertheless, Scrieciu (2007) notes the fact that auto-correlation is a major problem usually not considered in studies dealing with global analysis of the deforestation factors. The author shows that taking auto-correlation into account significantly decreases the strength of the empirical results.

Most studies focus on the aggregate influence of those factors on deforestation. However, as mentioned by Scrieciu (2007) and Damette and Delacote (2011), the fact that patterns of deforestation are difficult to identify globally has to be considered. A few studies analyze the deforestation drivers by clustering their sample (Leplay and Thoyer (2011), Culas (2007)). They suggest that the deforestation drivers may have various influence depending on the countries particularities. This gives the insight that the deforestation factors are strongly heterogenous. However, if one neglects this heterogeneity, then the mean OLS results cause bias, due to using a false estimation method. This issue has not been explicitly studied yet.

Our paper precisely assesses this problem, applying quantile analysis, notably developed by Koenker (2005). This methodology allows us to consider what are the patterns of the conditional heterogeneity of the deforestation factors by examining different quantiles of the conditional distribution of the deforestation rate. Furthermore, panel quantile regressions with fixed effects improve the usual cross-sectional or panel pooled data regressions by exploring simultaneously two kinds of heterogeneity: unobserved individual heterogeneity *via* fixed effects and common heterogeneity *via* covariates effects within the panel quantile estimation. In addition, we study the response of the deforestation distribution to some common exogenous shock on macro-economic variables like growth and exchange rate: what is the share of relatively low deforestation passing to high deforestation rates with such a common shock? Are the distributional aspects of the shock symmetric when the shock is positive or negative?

Section 2 presents an overview of the empirical studies on deforestation factors. Section 3 presents our quantile analysis and section 4 presents the distributional impact of a common shock. Section 5 discusses our results and research issues.

2 The empirical literature of the deforestation drivers

Since the beginning of the 1990's, the empirical literature has been ever growing, emphasizing a few factors of deforestation. At first, most papers focused on cross-section data. Then panel-data analysis started to be used more broadly. Some papers also chose to cluster their sample by continent or forest endowment, suggesting the heterogeneity of the deforestation drivers.

2.1 Which are the commonly estimated deforestation drivers?

Several socio-economic factors of deforestation have been cited and estimated at a global level. Those factors are usually considered as "underlying factors of deforestation" (Angelsen and Kaimowitz (1999)): they indirectly influence the deforestation agents, trough diverse transmission channels. Institutions, economic development, demographics and macro-economic factors are usually considered. Initial forest endowments is also a commonly cited pattern of deforestation.

Institutions: The term institutions usually encompasses the quality of public governance, political rights and freedom, corruption. This quite general term thus describes a lot of different realities. However the overall idea is that better institutions are related to better environmental management, forward-looking behaviors, higher efficiency and better enforcement of public policies. It follows that better institutions are related to lower deforestation. The seminal work by Deacon (1995) finds robust evidence of this relationship between institutional quality and deforestation. In his paper, Deacon shows that ownership risk provides incentive to increase deforestation. Barbier and Burgess (2001) notes the fact that corruption and institutional stability may be important institutional factors behind deforestation. Among others, Culas (2007), Nguyen-Van and Azomahou (2007), Bhattarai and Hammig (2001) find evidence that better institutions are related to lower deforestation.

Economic development: Relations between economic development and deforestation have been widely considered trough the Environmental Kuznets Curve (EKC) hypothesis. This hypothesis supports the idea of an inverted U-shaped curve relating income per capita and environmental degradation (Grossman and Helpman (1991)). In the early stages of development, economic growth is positively related to environmental degradation. However, once income per capita has reached a certain point, environmental degradation starts decreasing with growth.

When it comes to deforestation, studies find contradictory results on the EKC hypothesis. Shafik (1994) and Koop and Tole (1999) do not find evidence of this inverted U-shaped relationship. Using semi-parametric analysis, Nguyen-Van and Azomahou (2007) do not find this kind of relationship either. In contrast, Cropper and Griffiths (1994) do find an EKC for African and Latin American countries. Bhattarai and Hammig (2001) also find this relationship for African, Latin American and Asian countries. Culas (2007) only finds evidence of an EKC for deforestation in Latin America.

Demographics: Forests require space. People need space for their livelihood. The natural corollary is that countries with higher population density (especially rural density) and higher population growth experience higher rates of deforestation. Cropper and Griffiths (1994) is the seminal paper studying this link between population pressure and deforestation. The literature however usually finds little evidence that population pressure is positively related to deforestation.

Macro-economic factors: Other economic factors may influence land-use choices. Indeed, agricultural and timber prices, the real exchange rate, debt are likely to be related to the land use and deforestation. First, agricultural prices are related to higher agricultural productivity, which represents an incentive to agricultural expansion- agricultural expansion being the major direct cause of deforestation worldwide. Most papers find that higher agricultural prices are positively related to deforestation (Angelsen and Kaimowitz (1999)).

Second, the impact of timber prices is not straightforward. Higher timber prices may be seen as an incentive to protect forests and to implement sustainable forest management, since forests become more profitable. However, higher timber prices may also represent an incentive to illegal logging and unsustainable harvest, that may lead to land-use changes and deforestation. Cropper and Griffiths (1994) find that this second effect tends to dominate, while Chomitz and Thomas (2003) argue that the first effect dominates when land tenure is secure.

Finally, factors positively related with exports may lead to higher deforestation. For instance, structural adjustment (Capistrano and Kiker (1995)) and indebtedness (Kahn and McDonald (1995)) lead to policies aiming at increasing exports. In countries where agriculture is a major activity, those policies are likely to increase pressure on forest resources and increase deforestation.

Similarly, real exchange rate depreciation tends to increase exports, which may increase deforestation (Arcand et al. (2008)).

The forest-transition hypothesis: The forest-transition hypothesis can be related analytically to the convergence hypothesis. The idea is quite simple: countries with larger forest cover tend to experience higher deforestation rates. The intuition behind this theory builds on resource scarcity and marginal utility comparison. When forest cover is large, the marginal utility given to forest in the country is low, compared to agricultural land, which can be seen as an incentive to land conversion and deforestation. As long as the forest cover decreases (and deforestation takes place), the marginal utility given to forests increases (while the marginal utility given to agricultural land decreases). Deforestation is then supposed to end at the point at which the marginal utility of forests equals the marginal utility of agricultural land. Rudel et al. (2005) and Ewers (2006) investigate and find evidence of this relation between forest cover and deforestation. Considering forest endowments, Damette and Delacote (2011) show that countries with higher levels of timber harvesting tend to experience higher deforestation rates than others.

2.2 Empirical Methods

At the beginning of the 1990's, most papers used cross-section analysis to investigate the deforestation drivers. The main limit of this approach is that the time dimension is not taken into account. Conversely, since the beginning of the 2000's, panel-data analysis has emerged as a major tool to investigate the global deforestation factors. Panel data is more appropriate for econometric identification purposes. As far as we know, only Nguyen-Van and Azomahou (2007) use semi-parametric methods. Overall, most paper acknowledge the fact that country-wide deforestation data are of heterogenous quality and should be considered cautiously.

A few papers chose to take into account the countries heterogeneity, by clustering their sample. Most of the time, clustering has been made by continent (Culas (2007)). To our knowledge, only Leplay and Thoyer (2011) chose a cluster related to forest endowment to analyze countries heterogeneity. Scrieciu (2007) suggests that a generalized macroeconomic explanation of tropical forest depletion may be inappropriate, while Nguyen-Van and Azomahou (2007) show that countries heterogeneity is a major concern behind empirical multi-country studies of the deforestation factors. An important pattern of such clustering methods is their arbitrary nature: there is no clear way to prove that one clustering approach is more relevant than another.

To our knowledge, no paper investigate this issue of countries heterogeneity using quantile approach. Our analysis relies on this instrument to understand how countries differ in their deforestation patterns, and what are the sources of this heterogeneity.

3 The implementation of quantile analysis to deforestation patterns

3.1 Quantile regression methodology

Previous studies of the determinants of deforestation drivers employ classical econometric techniques. Traditional conditional mean approaches are used, estimating the conditional mean of Y given X: $E(y/X) = \alpha + X\beta$. Then β may be estimated by solving: $min \sum_{i=1}^{n}(y_i - x_i^T\beta)^2$, that is minimizing the mean squared errors.

In this paper, we use instead the quantile estimator and thus examine different quantiles of the conditional distribution of the deforestation rate. Using this methodology, we are able to examine the most and least deforesting observations and the most and least deforesting countries. For instance, it is of interest to evaluate the EKC for low and high quantiles of the distribution.

The quantile regression techniques have been developed by Koenker and Basset Jr. (1978) [1]. Following this approach, the previous conditional mean model can be rewritten for each τ quantile of interest as :

$$Q_y(\tau|X) = \alpha + X^T\beta(\tau) \tag{1}$$

Then, $\hat{\beta}(\tau)$ is derived by solving: $\min \sum_{i=1}^{n} \rho_\tau(y_i - x_i^T\beta)$. Therefore, we have as many estimators of β as values of $\tau \in [0,1]$ by changing the τ conditional quantile. The latter can be the median ($\tau = 0.5$), the mean as in OLS or any other quantile.

In the way of Koenker (2005), the previous quantile regression problem may be reformulated as a simple linear program as :

$$\min_{(\beta,u,v)\in[\Re^p\times\Re_+^{2n}]} (\tau 1_n^T u + (1-\tau)1_n^T v)|X\beta + u - v = y \tag{2}$$

where $\tau \in (0,1)$ and X denotes the usual $n \times p$ regression design matrix.

Conditional mean methods and quantile regressions can thus be summarized as two different optimization problems. Contrary to the usual minimization of the sum of squared errors in the OLS case, we minimize the weighted sum of absolute deviations in the quantile one. A singular

[1] See Koenker and Hallock (2001) and Koenker (2005) for surveys.

pattern of the quantile regression is that the residual vector is split into its positive and negative parts u and v respectively.

3.2 Panel Quantile regressions with fixed effects

Previous pooled data estimates do not take into account unobserved country heterogeneity. In this paper, we also perform panel-data quantile method with fixed effects, which allows to evaluate the conditional heterogeneous covariance effects of the deforestation drivers, while controlling for unobserved individual heterogeneity. Panel quantile regressions with fixed effects improve the previous pooled data analysis by exploring two kinds of heterogeneity: individual heterogeneity *via* fixed effects and common heterogeneity *via* estimating covariates effects within the panel quantile estimation. Although usual quantile methods - cross sectional or pooled data - are now well-known and lead to many applications, analogous fixed-effects ones have been developed recently, following the seminal work of Koenker (2004) [2]. Consequently, few papers have applied the corresponding fixed effects methods: to the best of our knowledge, the most popular papers who performed this method are Lamarche (2008) and Lamarche (2010).

The reason why this literature is very recent and still developing is that introducing fixed effects in quantile methods generates some specific concerns. Indeed, for a linear conditional regression with fixed effects, the within estimation allows the econometrician to eliminate the fixed effect by differentiating them out. However, in contrast to the mean regressions, the quantile method is not related to a linear operator. There is then an incidental problem, that is a problem of a large amount of parameters to estimate. As underlined by Galavao et al. (2010), the estimator will thus be inconsistent when the number of individuals goes to infinity while the number of periods is fixed[3].

Koenker (2004)[4] develops an appropriate methodology for panel data with fixed effects - called shrinkage method - and suggests a penalized quantile regression estimator. The special feature of this technique is to introduce a penalty term in the minimization to deal with the computational problem of estimating a large number of parameters (in our panel, we have 3 parameters * 8

[2] As a consequence, quantile fixed effects methods are not implemented in usual econometric softwares. We use R programming based on Koenker packages to perform the estimations in this paper.

[3] See Galavao et al. (2010) for asymptotic and bootstrap inference discussion and Ponomareva (2010) and Rosen (2011) for identification discussion.

[4] See also Koenker (2005) and Lamarche (2010) about penalized quantile regression estimators. Note that alternative approaches have also been developed: the Canay (2010) method does not require a penalty term whereas Galavao and Montes-Rojas (2010) developed quantile regression for dynamic panel data with fixed effects.

variables + 59 fixed effects = 83 parameters). In others words, the method consists of shrinking the individual fixed effects parameters, thanks to the penalty term, towards a common value to improve the performance (especially by decreasing the variability) of the covariance estimates.

In this methodology, parameter estimates are obtained by solving the following expression:

$$\min_{\alpha,\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{j=1}^{m_j} w_k \rho_{\tau_k}(y_{ij} - \alpha_i - x_{ij}^T \beta(\tau_k)) + \lambda \sum_{i=1}^{n} |\alpha_i| \tag{3}$$

where i is the index for countries (n), j the one for the number of observations per countries m_j, q is the index for quantiles, x is the matrix of explanatory variables (i.e. institution, growth, timber prices...), α^T is a vector of unobserved fixed effects and ρ_{τ_k} is the quantile loss function derived by Koenker and Basset Jr. (1978). In addition, w_k is a relative weight which controls for the contribution of the τ^{th} quantile on the estimation of the quantile fixed effects when we estimate simultaneously all the quantiles. We used here an equal wightening (0.25 for each quantile) when we estimate simultaneously[5] the quantiles 0.25, 0.5, 0.75 and 0.9. Finally, the last term of the minimization expression is essential and is called the penalty term. In this term, the λ parameter is a tuning parameter (Koenker (2004), Lamarche (2010)) which expresses the magnitude of the penalty term and helps to reduce the additional variability generated by the estimation of the individual fixed effects. Borrowing the Lamarche (2010) terminology, this parameter may be seen as controlling the vertical distance between the empirical conditional density function of the i^{th} country and the one of the pooled sample. The higher the λ parameter is, the closer to zero the fixed effects are for all i and then the empirical conditional function is close the pooled sample. In contrary, if the λ term goes to zero, the penalty term disappears and we get back the usual fixed effect estimator. In practice, the selection of λ is somehow arbitrary. In our estimates, we set λ to one as in Koenker (2004) but we conduct some sensitivity analysis. Setting the value of λ between 0.5 and 2[6] does not change significantly our results.

The results are displayed in table 3. To evaluate the significance of the estimates, we use panel bootstrap procedures in order to construct confidence bounds for the estimator[7].

[5]The estimation is simultaneous since the fixed effects are common and then constant among the estimated quantiles to solve for incidental problems.

[6]Lamarche (2010) used an empirically strategy based one a variance minimizing strategy.

[7]To this aim, we use the boot.rq procedure for R. Many thanks to Steve Mc Donald for programming assistance.

3.3 Comparing quantile analysis and conditional mean methods

In this section, we compare usual OLS regressions and quantile regressions. To this aim, we use a panel data set of 59 developing countries on the 1972-1994 period (N=59, T=23). The data set is in line with Nguyen-Van and Azomahou (2007) (see table 4 and **??**).

The results of OLS and fixed-effects regressions (OLS and FE respectively) are given in table 1, panel-pooled quantile regressions are given in table 2, and Panel Quantile regressions with fixed effects are given in table 3.

As a first comment, it is worthwhile noting that the continual mean methods give standard results of the literature on the deforestation factors: the EKC hypothesis only holds in the OLS regression and not in the FE regression; better institutions, lower harvest intensity and lower exchange rate are strongly negatively related to deforestation; population density and growth are not found to be robustly and significantly related to deforestation.

From this starting point, we consider the difference between those standard regressions and quantile analysis. Indeed, the panel-pooled quantile analysis brings more contrasted results. Overall, our variables of interest are significant only for high deforestation countries.

- We do find some evidence of an EKC for deforestation, when considering only quantile 0.6 to 0.9. The EKC hypothesis then seems to make sense when focusing on high deforestation observations (i.e countries and years).
- We have the same story considering the real exchange rate. It is only significant for higher quantile 0.6 to 0.9.
- Population density is positively related to deforestation for deciles 6 to 8, while considering timber harvesting, this is the case for deciles 7 and 8.
- Timber prices are negatively related to deforestation for the four last deciles: higher timber prices appear to represent an incentive for forest conservation in high deforesting countries.
- Growth is negatively related to deforestation only for the last decile.
- The institution variable is only significant at 12 % for decile 7 and 8. Nevertheless, we have to take into account the fact that institutions usually do not appear significant when not applying fixed effects methods.
- Finally, it is worthwhile noting that the magnitude of the coefficients increases for high deforesting countries (see figure 1).

Overall, not considering explicitly the conditional distribution of the deforestation process considerably blurs the results, and the quantile approach that we present in this paper is likely to bring new relevant pieces of evidence about the patterns of deforestation, and their implication with the level of deforestation. However, it is interesting to note that we find results similar to those of the standard regressions, but that they only apply for countries with larger deforestation levels.

From this statement, it is then possible to apply quantile regression with fixed effects. Indeed, panel quantile regressions with fixed effects improve the previous pooled analysis by exploring simultaneously two kinds of heterogeneity: unobserved individual heterogeneity *via* fixed effects and common heterogeneity *via* covariates effects within the panel quantile estimation. Here again, integrating fixed-effects method tends to reduce the significance of our results and brings some important conclusions on empirical assessment of the deforestation factors at a global level.

- Only the last quantile gets significant estimates. The deforestation patterns are then only significant for high-deforestation observations. It appears then that studies should focus on the countries with larger deforestation patterns. In contrast, deforestation is more difficult to analyze in countries where deforestation is a less important issue. This result bring the crucial insight that the factors usually considered in the literature are related to deforestation only in most vulnerable countries, in which deforestation is already a crucial concern.

- As under the pooled regression, growth is negatively related to deforestation for the last quantile. Then it seems that economic growth has no impact on deforestation for countries with lower deforestation levels. In contrast, it tends to reduce pressure on forests for most vulnerable countries with higher deforestation levels.

- Timber harvesting is still positively related to deforestation, but only for the last decile. Results given in the literature that more intensive harvesting brings more deforestation are then confirmed for most deforesting countries. This result may be related to the fact that more deforesting countries tend to rely more and depend more on forest harvesting than others.

- We do not find any evidence for an EKC and for the impact of population density, anymore. This result confirms most recent studies on the EKC for deforestation, which do not find strong and stable relationship between income per capita and deforestation. Therefore the cyclical component of economic development (growth) has more influence on deforestation than the structural one (GDP per capita).

- In contrast with most papers of the literature, institutions are not significantly related to deforestation. This may be due to the fact that institutions have low time variability. Their effect may thus be captured by the countries fixed effects.
- In contrast with the pooled regression, timber prices are now positively related to deforestation. The fact that the sign related to timber prices is not stable between the pooled and FE regressions is a striking result. A potential explanation is that the two methods may not capture the same type of effect. The pooled regression may capture the long run effect of timber prices (in the long run, if timber price increase, it is an incentive for forest conservation), while the FE approach better captures the short run effect of timber prices, because the FE capture the structural patterns of the countries that we consider (in the short run, higher timber prices are an incentive for higher harvest and then more deforestation).

Overall some important conclusions are brought by our quantile approach: (i) considering the distribution of deforestation and fixed effects is crucial when considering the deforestation factors; (ii) when applying quantile with fixed effects method, only 3 factors remain significantly related to deforestation: growth (-), timber harvesting (+) and timber prices (+); (iii) the deforestation factors are only significant for high deforestation observations, that is for most vulnerable countries in which deforestation is already a crucial concern.

The main crucial result of this study is that taking into account fixed effects and distributional aspects considerably reduces the significance of the results. This statement considerably emphasizes the difficulty to assess the global factors of deforestation and context-specific nature of deforestation patterns. As a corollary, it appears that previous studies may have over-estimated the importance of some factors (institutions, GDP per capita) and under-estimated the importance of others (timber prices and harvesting, growth).

Table 1: **Conditional mean methods**

	OLS	FE
GDP	3.40E-06***	2.24E-06
	(3.48)	(1.11)
GDP^2	-2.67E-10***	-9.34E-11
	(-2.80)	(-0.66)
Growth	-0.021*	-0.010
	(-1.68)	(-0.67)
Population Density	1.21E-05***	-2.64E-05*
	(2.84)	(-1.60)
Institution	0.0003	0.0008***
	(1.13)	(2.48)
Harvest	-0.0005	0.0069**
	(-1.37)	(2.04)
TCER	0.001	0.0037**
	(0.79)	(2.04)
Price	1.85E-05	7.21E-05
	(0.54)	(0.62)
Constant	-0.010	-0.087***
	(-0.96)	(-3.07)
DW	1.75	2.05
Adj R2	0.02	0.13

Figure 1: **Quantile coefficients process**

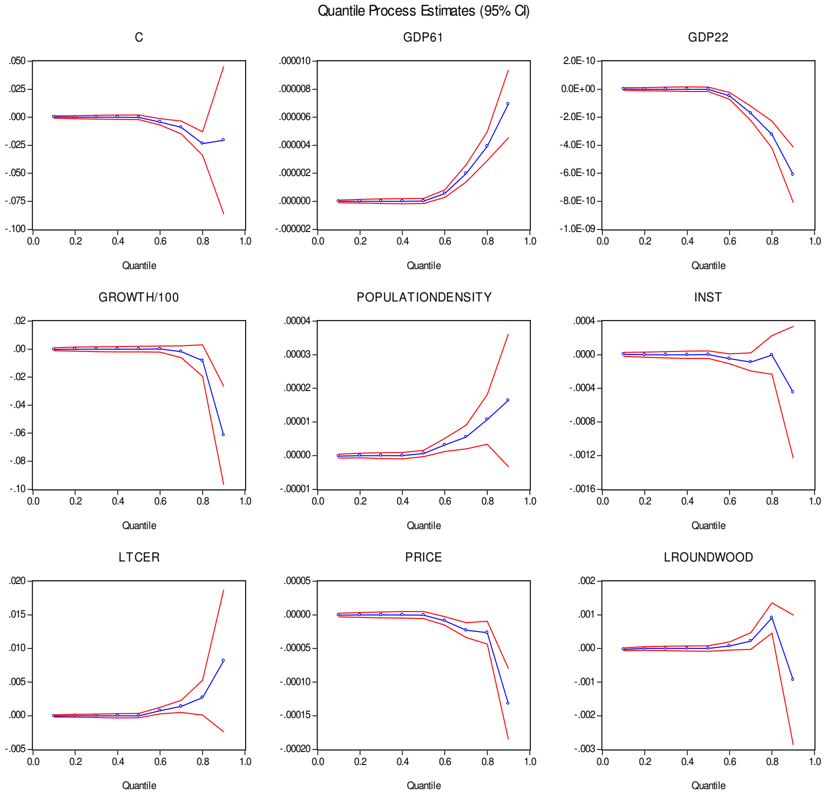


Table 2: **Pooled quantile regression**

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
GDP	-8.51E-09	6.62E-24	4.41E-39	3.92E-54	1.45E-08	5.46E-07***	1.99E-06***	3.92E-06***	6.95E-06***
GDP^2	1.28E-12	-4.04E-28	-3.59E-43	-1.99E-58	-1.10E-12	-4.80E-11***	-1.73E-10***	-3.24E-10***	-6.11E-10***
Growth rate	-0.000147	-2.71E-20	2.41E-35	-1.60E-50	1.39E-05	3.28E-05	-0.001838	-0.008252	-0.061424***
Population Density	-1.62E-07	2.65E-23	2.35E-38	2.09E-53	6.43E-07	3.18E-06***	5.56E-06***	1.08E-05***	1.64E-05*
Institution	4.49E-06	8.47E-22	2.82E-37	1.25E-52	9.03E-07	-4.80E-05	-8.68E-05	-2.71E-06	-0.000446
Harvest	-2.36E-05	-6.78E-21	1.50E-36	0.0000	-6.46E-07	7.34E-05	0.000223*	0.000908***	-0.000933
TCER	-3.68E-05	6.78E-21	6.02E-36	5.35E-51	1.70E-05	0.000764***	0.001400***	0.002701**	0.008151
Price	-5.69E-07	-3.18E-22	-4.70E-38	-1.51E-52	-4.91E-07	-8.83E-06***	-2.27E-05***	-2.65E-05***	-0.000132***
Constant	0.000320	0.000000	-2.71E-35	-1.07E-50	-0.000108	-0.004230***	-0.009078***	-0.023482***	-0.020437

Notes: Lower quantiles signify less deforesting countries. Huber Sandwich standards errors and covariance. The sparsity function is computed with a Kernel method.

Table 3: **Quantile regression with fixed effects**

	0.25	0.5	0.75	0.9
GDP	-1.10E-07	6.69E-11	4.23E-07	-6.53E-08
GDP^2	1.04E-11	6.57E-16	-3.73E-11	2.17E-12
Growth rate	-1.96E-04	-4.32E-07	-1.53E-04	-1.03E-04**
Population Density	-1.62E-06	-3.36E-09	2.09E-06	7.10E-06
Institution	9.04E-06	2.20E-08	1.05E-06	1.48E-06
Log Harvest	-1.03E-04	5.46E-07	2.55E-04*	1.01E-04**
TCER	-7.66E-09	-3.71E-09	-1.15E-06	3.15E-07
Price	-3.85E-05	2.04E-07	8.33E-05	3.87E-05**
Constant	-2.27	-2.26***	-2.23***	-2.28***

Notes: Lower quantiles signify less deforesting countries. ** denotes significance at 5 level.

4 Impact of a macro-economic shock on the deforestation distribution

In this section, we study the response of the deforestation distribution to a common exogenous shock on macro-economic variables, using coefficients presented in table 2 (the observed deforestation distributions are given in figures 2 to 4). To our knowledge, this is the first paper that performs this kind of methodology apart Dufrenot et al. (2010) about the trade-growth nexus. In our paper, we consider sequentially a shock on the real exchange rate, and a shock on growth.

Concerning the real exchange rate, an increase (resp. decrease) of the real effective exchange rate indicates an appreciation (resp. depreciation). We simulate sequentially a common positive shock and a common negative shock. For instance, a simulation of a common positive shock would be a common appreciation of the countries from the CFA franc zone. Indeed, because of its peg to the euro, the CFA franc has appreciated considerably over the last decade; we can also consider a common appreciation of the exchange rate of many developing countries. The goal of our simulation is to analyse the divergence in the reaction of those countries to a common shock and to outline the change in the deforestation distribution: many countries might be react differently to the same appreciation or depreciation and thus deforest more or less. Concerning the growth shock, we consider that many countries could be doped by a common positive (resp. negative) growth shock induced by a increase in the international economic trend (increasing the demand for wood...). Again, our aim is to analyse the divergence in the reaction of the countries to the same shock and to outline changes in the deforestation distribution.

First, when a positive shock on the real exchange rate happens, the distribution is less leptokurtic after shocking the exchange rate whatever the sign of the shock. Then a large positive shock on the real exchange rate is likely to increase the number of countries with high deforestation rates (figure 2). Note however that the shock has to be important enough to experience a shift in the distribution, and that the average deforestation rate keeps lying around 0. Obviously, a larger shock (figure 2) leads to a more pronounced dispersion of the deforestation rates. Finally, a negative shock brings similar result on the left-side of the distribution (see figure 3). Those distributional impacts of a shock on real exchange rate can be explained as follow: one can expect that countries' agricultural sector will benefit from better trade opportunities, which may create an incentive for larger exports, and then larger agricultural expansion and deforestation (Arcand et al. (2008)). Thus, some countries that were not competitive enough to export on international markets may increase their exports, due to the shock on real exchange rate. Those countries may thus switch from low deforestation rates, to higher ones, when the real exchange rate passes the threshold at which those countries become competitive.

When an exogenous shock on growth is introduced (figure 4), the results are a bit different. Indeed, with a shock on growth (positive or negative), the distribution of deforestation keeps being symmetric. This may be due to the fact that, in contrast to a shock on real exchange rate, there is no threshold effect that make the distribution shift on one side. In this case, we just note that the distribution of the deforestation rates becomes more dispersed. Then a shock on growth tends to reduce deforestation in some countries, while increasing it in others. Moreover, the magnitude of the impact is smaller. Indeed, growth is only significant for the last quantile of the distribution, which limits the distributional aspects of a growth shock.

Figure 2: **Deforestation Conditional Distribution (positive shock on exchange rate)**

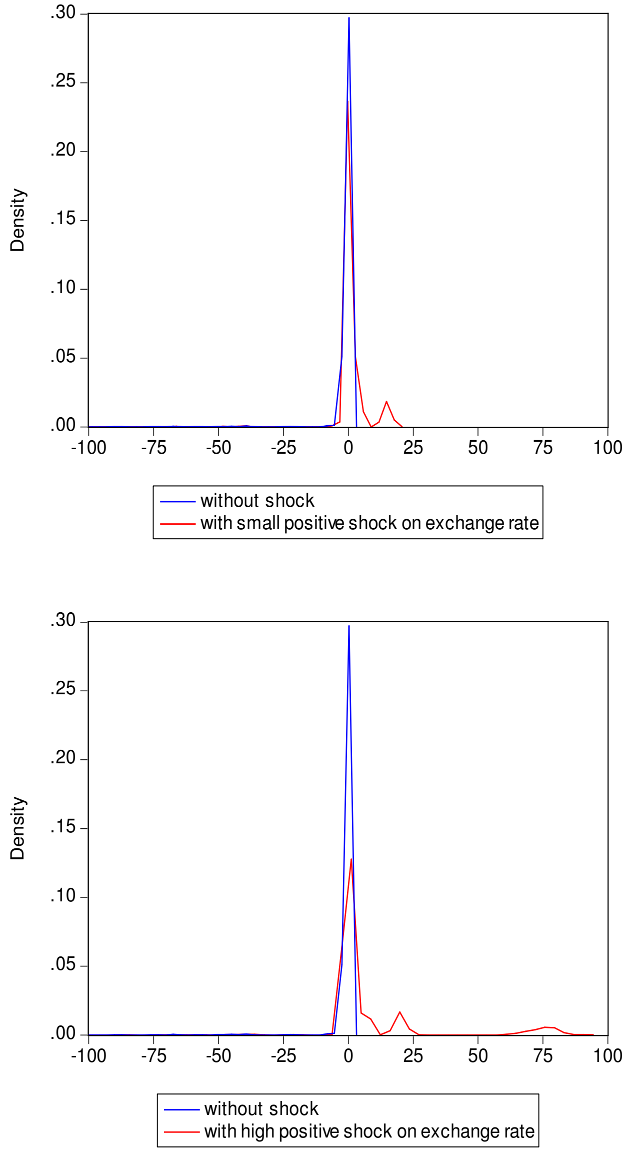


Figure 3: **Deforestation Conditional Distribution (negative shock on exchange rate)**

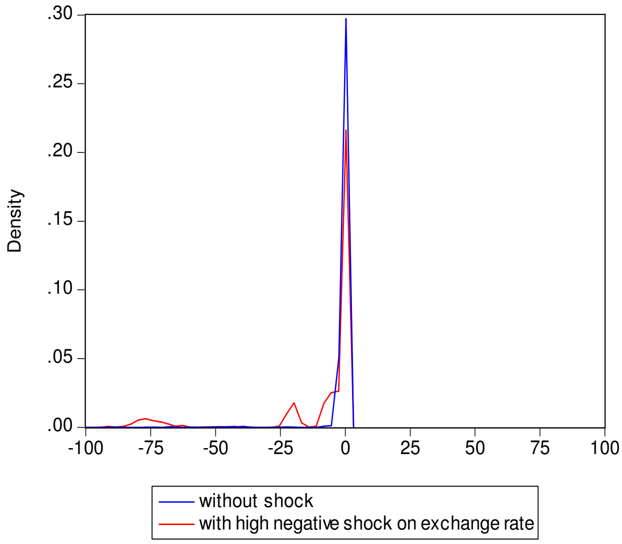
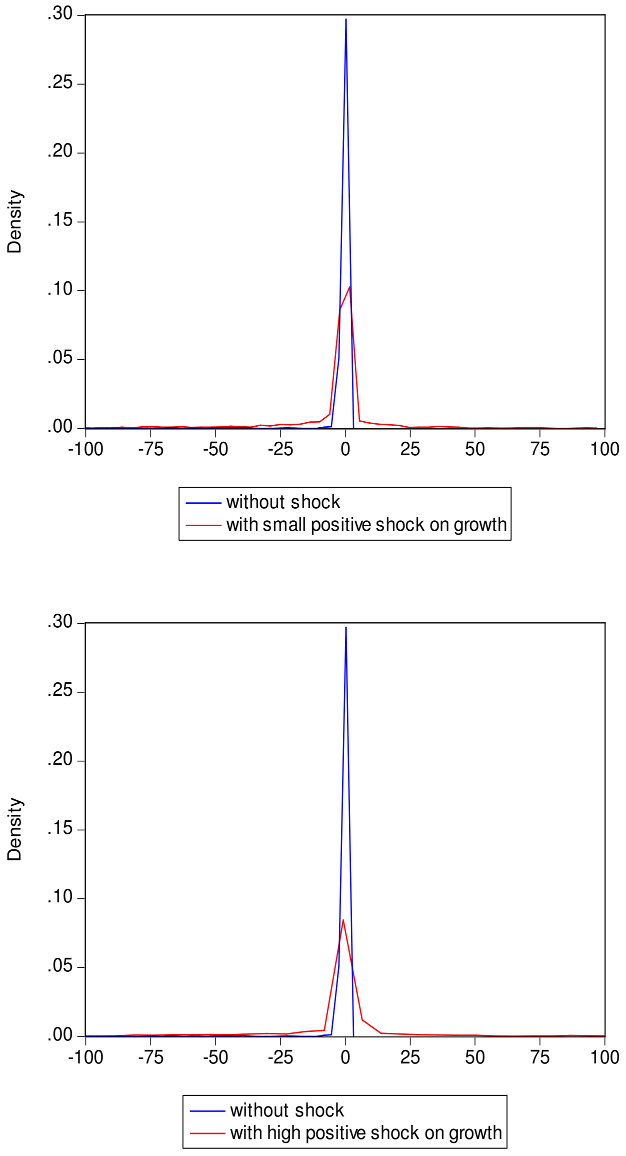


Figure 4: **Deforestation Conditional Distribution (positive shock on growth)**



5 What can be learned from quantile analysis?

Are country-level deforestation studies at a global level a relevant tool? In this paper, we show the high heterogeneity among deforesting countries, which may prevent from using such type of analysis. Nevertheless, a better understanding of such a global phenomenon is required in order to better deal with it and to implement relevant policies. This implies a crucial tradeoff between the needs to have a better understanding of what drives deforestation in developing countries, and the huge difficulty to assess those drivers.

We argue in this paper that the quantile-based approach can bring relevant information about deforestation processes. Indeed, we show that some deforestation factors happen to be more important in countries that deforest the most: timber harvesting, timber prices and growth especially. This gives the insights that those factors have been underestimated in previous studies and that they have an impact on deforestation only in most vulnerable countries, where deforestation is already an important concern. Therefore, helping countries to transit from high deforesting quantile to lower ones may be done by reducing tensions on the forest sector, better valorizing forest products (through timber certification), and favoring economic development. Nevertheless it appears that those incentives would not be sufficient to overcome the problem of deforestation, which is mainly driven by fixed effects. Moreover other factors appear to have been over-estimated in the past, such as institutions or GDP per capita. Then it appears that countries heterogeneity creates artifacts on those usually considered deforestation drivers. For instance, stable and general variables such as institutions may have been found to be significant only because they were hiding fixed effects.

Overall, considering unobserved heterogeneity and distributional aspects into account considerably emphasizes the difficulty to assess deforestation factors at a global level. Indeed, context-specific and unobserved heterogeneity proves to be more important deforestation drivers than global ones. In order to better understand deforestation dynamics, there is then a crucial need to invest in microeconomic and local studies to better understand the contextual drivers of deforestation. At the same time, empirical studies considering the deforestation factors at a cross-country level should take care of taking those kinds of heterogeneity into account.

Finally, we show that the distribution patterns of deforestation may be impacted in a different way by a macro-economic shock. While a shock of the real exchange rate shifts the distribution of deforestation on one side, a shock on growth only tends to increase the dispersion of the distribution, but keeping it symmetric.

Table 4: **Variable description**

Variable	**Definition**	**Source**
Deforestation	Yearly Percentage of variation of the forest cover	FAO
Harvest	Log of the volume of roundwood harvested	FAO
Price	Yearly average price of timber	FAO
Civil liberties	"Freedoms to develop views, institutions, and personal autonomy apart from state", Index from 1 (high) to 7 (low)	Freedom House
Political rights	"Permitting people to freely take part in the political process that represents the method by which the policymakers are chosen to make effective decisions, Index from 1 (high) to 7 (low)	Freedom House
Institutions	Sum of *Civil liberties* and *Political rights*	
GDP	Gross Domestic Product per capita	Penn World Table 6.1
Growth	Annual percentage growth rate of GDP at market prices based on constant local currency	World bank tables
Population density	People per squared km	World Bank tables
TCER	Real Exchange Rate	World Bank tables

Table 5: **Descriptive statistics**

Variable	Mean	Standard Deviation	Min	Max
Deforestation rate	0.002	0.018	-0.184	0.228
Roundwood	19052	46411	14	312788
Average price	28.6	9.82	11.6	63.0
Institutions	8.75	3.28	2	14
GDP	3437.8	2693.1	330.4	21249.8
Growth	0.89	5.23	-28.60	23.60
Population density	92.5	135.2	3.1	964.7
TCER	141.9	58.4	30.3	478.3

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Contact us :
Chaire Economie du Climat - Palais Brongniart (4e étage)
28 Place de la Bourse, 75 002 Paris
Tel : +33 (0)1 49 27 56 34
Fax : +33 (0)1 49 27 56 28
Email : contact@chaireeconomieduclimat.org

Working Papers Publication Director: Pierre-André Jouvet

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