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3 Deforestation: correlations, possible causes and 4 some implications

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11 SUMMARY

12 Changes in national forest areas during 1990-2000 are contrasted with other variables to
13 illustrate correlations and provoke discussion about possible causes. Twenty-five
14 statistically-significant correlations (including rural population, life expectancy, GDP,
15 literacy, commerce, agriculture, poverty and inflation) are illustrated and a statistical
16 model suggests that good governance, alternative employment opportunities, and
17 payments for environmental services may be effective in combating deforestation. The
18 data suggest that a global forest convention may need to be supported by substantial and
19 carefully-targeted development assistance to foster good governance.

20 *Keywords:* deforestation, global forest convention, governance, payments for
21 environmental services

22 INTRODUCTION

23 The United Nations Forum on Forests (UNFF) seeks to secure a global forest
24 convention to help curb deforestation. These efforts began in 1990, with calls for such
25 an agreement appearing in the 1990 São Paulo Declaration of the Intergovernmental
26 Panel on Climate Change (IPCC 1991), in reviews of the Tropical Forestry Action Plan
27 (Dembner 1991), in a fact sheet of the former US President George Bush (1990), and as
28 a call from the G7 for a “global forest convention ... to curb deforestation, protect
29 biodiversity, stimulate positive forestry actions and address threats to the world's
30 forests” (G7 1990). Agreement could not be reached at the Earth Summit in Rio de
31 Janeiro in 1992 (the compromise was a “Non-binding authoritative statement on forest
32 principles”), and negotiations have continued fruitlessly with progress toward a
33 conclusion appearing imperceptible. The most recent setback was in May 2005, when
34 the United Nations Forum on Forests (UNFF) failed to get agreement on “the
35 parameters of a mandate for developing a legal framework on all types of forests”
36 (UNFF 2000). Advocates argue that a convention would ensure that all of the world's
37 forests are sustainably managed, provide the basis for a common understanding of
38 sustainable forest management, and establish the legal framework for monitoring and
39 compliance (e.g., Roberts 2003). Critics contend that the proposal addresses the wrong
40 issues, and does not provide an adequate means to regulate the private sector (e.g.,

41 Jeanrenaud *et al* 1997). There is little reliable evidence to inform this debate. The
42 pursuit of reliable data tends to lead researchers to sub-national or regional-scale studies
43 in a few selected countries (Angelsen and Kaimowitz 1999), but this introduces new
44 problems including the possibility of bias and a reduced ability to generalize. In
45 contrast, this study draws on a global database to offer a broad overview and to
46 stimulate discussion on deforestation.

47 This paper presents an overview of trends evident in recent global data. It makes no
48 attempt to review the extensive literature on deforestation; instead readers are
49 encouraged to consult the comprehensive reviews by Wibowo and Byron (1997),
50 Kaimowitz and Angelsen (1998), Angelsen and Kaimowitz (1999), Barbier and Burgess
51 (2001), and Geist and Lambin (2002, 2003). In their comprehensive review of 146
52 economic models of deforestation (and some 200 literature references), Kaimowitz and
53 Angelsen (1998) challenged many conventional hypotheses about deforestation. They
54 found that most researchers agreed that more roads, higher agricultural prices, lower
55 wages, and a shortage of off-farm employment generally led to more deforestation, but
56 that the effects of agricultural input prices, household income levels, tenure security,
57 population growth, poverty reduction, national income, economic growth, and foreign
58 debt were unclear. They criticized the weak methodology and poor data of many models
59 which, they felt, make results questionable. Kaimowitz and Angelsen (1998) were
60 particularly critical of global regression models, because of limited and poor data,
61 inability to distinguish between correlation and causality, inappropriate assumptions
62 regarding the normality of data, and the dilution of micro-level patterns during the
63 aggregation of data. These concerns serve as a caveat on the conclusions that may be
64 drawn from global databases, but should not inhibit such analyses. The Forest Resource
65 Assessment 2000 (FRA 2000) is an improvement on previous global inventories
66 (Mayaux *et al.* 2005), has sufficient degrees of freedom to allow examination of several
67 variables, and is easily transformed to a normal distribution that satisfies statistical
68 assumptions (see Figure 1 below). It is clear that weaknesses remain, both in the FRA
69 2000 data, and in the assumption that national averages are informative of deforestation
70 trends. Thus this paper draws attention to patterns evident in the data (rather than to
71 estimated parameters), so that readers can judge for themselves the adequacy of the
72 database. This paper is not a comprehensive review, but seeks to complement existing
73 reviews by presenting empirical data at the global scale in an accessible format to
74 stimulate discussion.

75 DATA

76 This study draws on data from the Forest Resource Assessment 2000 (FRA 2000) of the
77 United Nations Food and Agriculture Organization (2002). The FRA 2000 documents
78 the change in forest area in over 200 countries during the decade 1990-2000. Note that
79 the FRA 2000 is concerned with the area forested land, and may not reveal situations
80 where primary forest has been replaced with forest plantations. The reported rate of
81 change varies from -9% per year in Burundi to +9% per year in Cape Verde. These rates
82 of change are over-dispersed (with many values close to zero, and few values exceeding
83 $\pm 5\%$) and violate the conventional statistical assumption of normally-distributed

84 residuals. Thus the data were normalized using a square-root transformation (or $-\sqrt{|x|}$
85 where rate of change was negative). The resulting data distribution is close to normal
86 (Figure 1), and was used as the response variable in this study, here abbreviated as
87 *afforestation*. It can be converted to a rate of change simply by squaring and restoring
88 the sign. Thus a response of -3 corresponds to a -9% annual change in forest area and a
89 deforestation rate of 9% per year.

90 **[Figure 1 near here]**

91 Transformations are also appropriate for some of the predictor variables (sometimes
92 called 'independent' variables). For instance, with the untransformed population density
93 data (Figure 2), one nation with a high population density (Singapore) has a huge
94 influence on the assumed trend (statistically, it has strong leverage), and the use of a
95 logarithm transformation allows all the data to have a more equal influence on the trend.
96 Such a transformation is also appropriate because a few additional people will have a
97 greater effect in an area with low density than in an area with an already high density.
98 Notice that the transformation has a dramatic effect on the apparent correlation with
99 tropical afforestation (Figure 2, solid line), changing it from +10% to +1%.

100 **[Figure 2 near here]**

101 The area associated with each datum varies greatly, ranging from about 1000 ha in the
102 Maldives to 850 million ha in the Russian Federation. If the objective was to establish
103 an unbiased estimate of the rate of deforestation, it would be appropriate to weight data
104 according to the area represented. However, the present study is concerned with
105 potential causes of deforestation, so each country was treated equally, and no weights
106 were used.

107 There is a strong correlation between the response and latitude ($r = 55\%$, $P < 0.0001^1$),
108 with much of the reported deforestation occurring in the tropics (Figure 3). A similar
109 correlation ($r = -56\%$) is obtained with a binary variable that denotes tropical countries
110 as those for which the geographical centroid lies within $\pm 25^\circ$ of the equator. Since many
111 other variables of interest are correlated with both the response and with latitude, both
112 global and tropical trends are reported and illustrated.

113 **[Figure 3 near here]**

114 Inferences drawn from the FRA 2000 data should be tempered by the realization that
115 these data reflect observations of forest change during a single period (1990-2000) in
116 many different places. When a correlation (e.g., between rural population and

¹ The correlation coefficient r indicates how well a trend fits the data (0 indicates that there is no trend and a simple average suffices; $\pm 100\%$ indicates a perfect fit; the sign indicates whether the trend increases or decreases), and the probability P indicates the likelihood that the trend is due to chance. A good result has a large r (ignoring the sign) and a small P . It is conventional that P should be less than 0.05, which signifies a 1 in 20 chance of attributing a correlation when one does not really exist.

117 afforestation) is noted, one is tempted to infer causality (e.g., that an increase in the
118 rural population will lead to more deforestation), but this does not necessarily follow.
119 The FRA 2000 data certainly show that many nations which experienced a reduction in
120 forest area during 1990-2000 also have a relatively high proportion of their population
121 in rural areas. However, the rural population need not be the cause, and need not be
122 associated with the deforestation. Indonesia is one of the nations with a deforestation
123 rate exceeding 1% and with a rural population of 60%. However, most of Indonesia's
124 rural population live on the island of Java (which has 60% of Indonesia's population on
125 7% of the land area), and most of the deforestation occurred on other islands (e.g.,
126 Kalimantan; Fuller *et al* 2004), so it is unlikely that the rural Javanese were a direct
127 cause of Indonesia's deforestation. Clearly, caution is required in drawing inferences
128 from the FRA 2000 data, especially regarding possible causes of deforestation, and in
129 speculating whether similar trends may arise in other situations.

130 There are other limitations of the FRA 2000 data. The reliability of deforestation
131 estimates varies by countries; the estimates for some countries are based on repeated
132 inventories, whereas for other countries, estimates were inferred indirectly and are less
133 reliable. Such weaknesses in the data may inflate error estimates (and thus weaken any
134 tests of significance), but have relatively little influence on the trends, because the data
135 illustrated in Figures 3-17 did not contain points with high leverage.

136 RESULTS

137 Key results are summarized in Table 1, which is divided into two parts to show the
138 correlation of selected indicators with afforestation (square root of the rate of change in
139 forest area) worldwide, and in the tropics. This distinction between global and tropical
140 trends is drawn partly because latitude is the variable with the strongest correlation with
141 afforestation, and partly because many researchers are concerned primarily with tropical
142 deforestation.

143 Treaties

144 Ruis (2001) identified ten international treaties that should contribute towards
145 conservation outcomes, but there is no evidence that these treaties have been effective
146 (Table 1, Figure 4). There is no indication that afforestation increases amongst nations
147 that sign more of these treaties; on the contrary, a significant correlation ($r = -18\%$, $P =$
148 0.04 , Table 1) points to that fact that some parties to the treaties are amongst the
149 countries that lost most forest during 1990-2000.

150 The ten treaties identified by Ruis (2001) are the Convention on Wetlands of
151 International Importance especially as Waterfowl Habitat (Ramsar, 1971), Convention
152 concerning the Protection of the World Cultural and Natural Heritage (1972),
153 Convention on the International Trade in Endangered Species of Wild Flora and Fauna
154 (CITES, 1973), Vienna Convention for the Protection of the Ozone Layer (1985),
155 Convention Concerning Indigenous and Tribal Peoples in Independent Countries
(1989), *Convention on Biological Diversity* (1992), *United Nations Framework*

157 *Convention on Climate Change* (1992), International Tropical Timber Agreement
158 (1994), *United Nations Convention to Combat Desertification in those Countries*
159 *experiencing Serious Drought and/or Desertification, particularly in Africa* (1994), and
160 the Agreement Establishing the World Trade Organization, (1994).

161 Ruis (2001; see also Sayer *et al.* 2000, Innes and Er 2002) argued that three of these
162 treaties (those in *italics*, namely Biodiversity, Climate Change, and Desertification)
163 should impose a particular obligation to conserve forest, but a test of the efficacy of
164 these treaties (collectively or individually) is meaningless (and as expected, not
165 statistically significant at $P=0.7$), because the test hinges on afforestation trends in a
166 handful of countries that did not sign (mainly those that did not sign the Desertification
167 treaty). The test of the ten treaties collectively is fraught with the same difficulty: the
168 test result hinges largely on whether or not nations signed the Convention on Wetlands
169 of International Importance (Ramsar, 1971) and the International Tropical Timber
170 Agreement (1994). While the former is concerned with wetlands (and waterfowl) and
171 may not impinge on forests, the latter is clearly pertinent to tropical forests.

172 **[Figure 4 near here]**

173 Figure 4 is thought-provoking, but is not unambiguous. Proponents of a forest
174 convention may draw on Figure 4 to argue that existing treaties do not protect forest,
175 and that a specific forest convention is needed. Skeptics can argue that existing treaties
176 (such as the International Tropical Timber Agreement 1994) have not reduced
177 deforestation, so it is fanciful to assume that a forest convention will be more
178 successful. Proponents may counter that it is premature to judge conventions which
179 came into force in the middle of the monitored period (1990-2000). Skeptics may
180 respond that negotiations commenced well before the 1990 baseline, and that serious a
181 commitment by signatories and ratifiers should have become evident in the FRA 2000.
182 The reality may be that many other factors mask any effect of the treaties considered
183 here. While one cannot, and should not, assert that the treaties are making things worse,
184 it is clear that the FRA 2000 offers no evidence that these treaties are helping to reduce
185 deforestation. That lack of evidence may arise because of limitations in the FRA 2000
186 data, because of insufficient time for the effect of treaties to become evident, or because
187 of the scope and implementation of the treaties.

188 **Development assistance**

189 It is often assumed that development assistance can be influential in halting
190 deforestation, but the evidence for this is equivocal. Estimates of official development
191 assistance reported in the CIA World Factbook (2004; reflecting net official
192 development assistance in ± 1999 from OECD nations to less developed nations, that is
193 concessional in character, seeks to promote economic development, and contains a grant
194 element of at least 25%) suggest a positive correlation between aid (per capita) and
195 tropical afforestation ($r = 23\%$, $n=114$, $P=0.01$), whereas 1998 estimates reported by the
196 World Bank (2000) suggest a weak negative correlation ($r = -17\%$, $n=90$, $P=0.1$). The
197 different trends reflect different kinds and sources of assistance, different time-frames,
198 and different nations. A standardized set of nations common to both data sets is too

199 small to offer meaningful insights (n=77, P>0.2). The pooled data set indicates a
200 positive relationship in the tropics (r = 18%, n=158, P=0.04, Figure 5), but a negligible
201 relationship at the global scale (P=0.2). Clearly, cash is no panacea, and context is
202 critical if development assistance is to be effective (e.g., Easterly 2001).

203 **[Figure 5 near here]**

204 **Correlations with deforestation**

205 Vanclay and Nichols (2005) commented on the strong relationship between gross
206 national product, rural population and afforestation, and illustrated that both rural
207 population (%) and Log(GNP/capita) exhibit a linear trend with afforestation. The trend
208 holds when both variables are fitted simultaneously to the FRA 2000 data:

$$209 \quad \text{Response} = 0.09 \text{ Log(GNP/capita)} - 0.02 \text{ RuralPop} \quad (1)$$

210 While prediction of the rate of forest area change is imperfect, the equation offers a
211 reasonable ability to classify nations as afforesting or deforesting (Figure 6).

212 **[Figure 6 near here]**

213 Equation 1 and Figure 6 correctly classify 132 of 152 nations. It is interesting to
214 examine the mis-classified nations more closely. Nine nations deforest during 1990-
215 2000, even though their GNP and rural population anticipate afforestation. All of these
216 nations have problems with corruption (Chile is the least corrupt, with a corruption
217 perception index of 6.9; Transparency International 2000), and the level of corruption is
218 correlated with the distance from the break-even line (r = -19%, P = 0.3), suggesting
219 that corruption may play some role in explaining the departure from the expected trend.
220 It is more difficult to explain the 21 nations that afforest during 1990-2000 despite
221 indications to the contrary. These nations include Bangladesh, India, Vanuatu, Vietnam,
222 etc. Of several variables examined (including relative area of forest, energy
223 consumption and literacy), the most informative appeared to be energy consumption
224 (kg/capita oil equivalent; World Bank 2000), with 11 of the 21 nations for which data
225 are available exhibiting a strong correlation (r = -80%, P = 0.001) between energy use
226 and departure from the break-even line. It is conceivable that these exceptional 21
227 nations may rely on wood for fuel (e.g., cooking, heating, sterilizing water), and their
228 citizens may have a personal interest in maintaining the fuelwood resource and in
229 increasing the area of forest. These and other observations suggest that the FRA 2000
230 data offer some utility for testing hypotheses concerning causes of and solutions to
231 deforestation. Thus a more detailed examination of deforestation trends was undertaken.

232 Easterly (2001) argues that incentives are necessary for development. They are also
233 necessary to halt deforestation, but they are not sufficient. Halting deforestation also
234 requires the creation of opportunities (e.g., in the form of employment more attractive
235 than cultivating crops and harvesting timber), and fostering the ability to realize those
236 opportunities (e.g., provision of basic services including education, health and transport;
237 in short, good governance; Vanclay 1993, Vanclay and Prabhu 1997). What follows is
238 not an exhaustive search for correlations, but an attempt to shed light on the hypothesis
239 that afforestation is related to these opportunities and services.

240 **Alternatives to deforestation**

241 Table 1 summarizes key results. Entries in Table 1 can be grouped into several
242 categories encompassing concepts of alternatives (to primary agriculture and timber-
243 getting), governance, health, wealth and information. The correlation between
244 afforestation and rural population may well reflect alternatives to agricultural pursuits.
245 This possibility is also reflected in many other variables in Table 1, including internet
246 access, CO₂ emissions, international reserves, commercial services, electricity
247 consumption and industrial value-adding, all of which are significant in the tropics
248 ($P \leq 0.05$), and most of which are significant at the global scale. The ability to use the
249 internet (Figure 7) does not imply that people are deforesting in simulation games rather
250 than in reality; rather, it reflects the capacity and skill available for employment outside
251 the agriculture and lumber sectors. Similarly, higher CO₂ emissions do not imply that
252 people are burning fossil fuel rather than forests, but reflect the job opportunities
253 available in the industrial sector.

254 **[Figure 7 near here]**

255 Other, more direct indicators of alternative employment include exports of commercial
256 services and industrial value-adding (both $P \leq 0.05$, Table 1 and Figure 8).

257 **[Figure 8 near here]**

258 It is interesting that the national unemployment rate (%) is not well correlated with
259 afforestation in the tropics ($r = -10\%$, $P = 0.2$), even though it is significant at the global
260 scale ($r = -27\%$, $P = 0.0006$, Table 1). This may be because urban and rural
261 unemployment rates may be quite different, and may reflect that it is rural
262 underemployment (and lack of other income-producing alternatives) rather than urban
263 unemployment that contributes to deforestation. The correlation may also be
264 confounded by different definitions of unemployment in different countries.

265 **Intensifying agriculture**

266 Some deforestation is caused by agricultural expansion, and intensification of
267 agriculture rather than expansion of agricultural lands may help to reduce deforestation.
268 As Angelsen and Kaimowitz (2000) have pointed out, making agriculture more
269 profitable can be a two-edged sword, as it may simply allow agriculture to encroach
270 onto still more remote and more marginal forest lands. However, there is some evidence
271 that increasing agricultural productivity by fostering more value-adding per worker, can
272 help to reduce deforestation ($r = 31\%$, $P = 0.01$, Table 1 and Figure 9). However, simply
273 expanding the agricultural sector without commensurate investment in other areas is
274 likely to be counterproductive, as afforestation tends to decrease as the agricultural
275 share of GDP increases ($r = -33\%$, $P = 0.005$, Table 1 and Figure 9).

276 **[Figure 9 near here]**

277 **Health**

278 Table 1 shows that life expectancy and infant mortality are significant ($P < 0.001$), both
279 in the tropics and globally (Figure 10). It is unlikely that longer life-spans cause people
280 to think more carefully about forest depletion; it is more likely that life-span and other
281 health indicators also indicate the efficacy of government services (if nothing else
282 works, we cannot expect wise management of forests), the ability of people to gain
283 alternative employment, and the demand for fuelwood to sterilize water. The World
284 Bank's (2000) estimate of access to improved water is positively correlated with
285 afforestation, but is significant only at the global scale (Table 1).

286 **[Figure 10 near here]**

287 **Wealth**

288 Wealth, both personal and national, also influences deforestation, because wealthy
289 people and nations have more options for using and managing resources. This is evident
290 in the afforestation trend with domestic savings and international reserves, both of
291 which are positively correlated with afforestation (Figure 11).

292 **[Figure 11 near here]**

293 The wealth of individuals and families also affects the propensity to deforest, and this is
294 evident in the trend exhibited by poverty (% of national population below the poverty
295 line), rural poverty (% of rural population below the poverty line), and in the Gini
296 coefficient (an index of equality, in which 0 implies wealth is equally shared and 1
297 implies that all the wealth is in the hands of one person; e.g., Sweden has a Gini index
298 of 25, and Brazil has 60). Globally, the Gini index has a good correlation with
299 afforestation ($r = -53\%$, $P < 0.0001$, Table 1 and Figure 12), but the correlation is weak
300 within the tropics and it is not clear if this indicator is useful in explaining deforestation
301 patterns. In contrast, and despite a small sample size, the correlation between rural
302 poverty and afforestation is significant both in the tropics and globally ($P < 0.05$, Table 1
303 and Figure 12), and may reflect that those with no better alternatives, resort to using
304 (and perhaps clearing) forest to earn an income.

305 **[Figure 12 near here]**

306 **Information**

307 The ability to realize alternatives requires information, both to enable people to find
308 jobs, and to envisage new business opportunities. Thus there should be a correlation
309 between afforestation and information services. In Table 1 and Figure 13, we see
310 significant correlations with adult literacy, internet use and daily newspapers ($P \leq 0.02$).
311 Other indicators offer a correlation similar to that of literacy (e.g., expected years of
312 schooling) and daily newspapers (e.g., radio and telephone ownership). Clearly, these
313 indicators reveal not only access to information, but also disposable income and the
314 efficacy of basic services.

315 **[Figure 13 near here]**

316 **Government services**

317 In some developing countries, few services work properly, so it is no surprise that
318 forestry does not work as it should. Forest management does not stand in isolation, so
319 halting deforestation also means getting government services to work. This is evident in
320 several entries in Table 1, including the correlations with electricity consumption and
321 paved roads (Figure 14). The correlation with paved roads is an indication of the ability
322 of a society to provide and maintain infrastructure, not an indication that paved roads
323 are the path to forest conservation. One should not assume that paving the trans-
324 Amazon highway will help to reduce deforestation (it is likely to have quite the opposite
325 effect!). The inference that should be drawn is that a society with the financial and
326 intellectual resources to pave and maintain roads should also have the ability to provide
327 incentives to manage forests wisely. Similarly, consumption of electricity reflects the
328 ability of society to maintain an electrical distribution network, the presence of industry,
329 and of households wealthy enough to have electrical appliances.

330 **[Figure 14 near here]**

331 **Confidence**

332 Forestry is a long-term enterprise, and conserving forests requires confidence in the
333 future. Hence concern for, and conservation of forests requires people who are not pre-
334 occupied with finding their next meal, and governments and investors who have
335 confidence in the future. There is ample empirical data to support this contention. Both
336 foreign investment and credit rating are correlated with the propensity to afforest
337 (Figure 15). The trend with foreign investment holds for both total and relative
338 investment (i.e., per capita or per unit GDP).

339 **[Figure 15 near here]**

340 **Population**

341 One-quarter of recent studies attribute deforestation to population (Rudel *et al* 2000), so
342 it is appropriate to examine the correlation between afforestation and population. FRA
343 2000 data suggest that population density has a negligible effect on deforestation, both
344 in the tropics and world-wide ($P>0.5$), although there is some evidence that rapid
345 population growth may contribute to deforestation (Table 1 and Figure 16).

346 **[Figure 16 near here]**

347 **Subsidies**

348 Subsidies have received much attention, and are generally viewed as detrimental to
349 forests (e.g., Browder 1985). However, the FRA 2000 data offer a different view. Figure
350 17, based on World Bank (2000) data, reveals that most countries that afforest have

351 subsidies exceeding 20 percent of total government expenditure, and that many
352 countries that deforest have lower subsidies. The correlation between subsidies and
353 afforestation is significant at the global scale ($r = 53\%$, $P < 0.0001$), and comparable
354 within the tropics ($r = 21\%$, $P = 0.1$, Figure 17). The trend holds for subsidy data from
355 1990, 1997, and for the average of both these years. This does not imply that an increase
356 in subsidies will reduce deforestation; it may simply reflect the fact that nations that can
357 afford such subsidies are wealthy nations that have already solved their deforestation
358 problems in other ways. However, it does suggest that the role of subsidies in managing
359 deforestation should be reconsidered.

360 **[Figure 17 near here]**

361 **Synthesis**

362 Clearly, there are many factors that may help to explain observed patterns of
363 deforestation, alone or in conjunction. This study commenced by exploring single
364 factors, but it can be informative to consider several factors in conjunction (cf. Figure
365 6). Such analyses are not straight-forward, because the available data contain many
366 correlated variables (cf. life expectance and infant mortality, Figure 10), and there may
367 be no single 'best' explanation of the observed trends. Nonetheless, conventional
368 stepwise linear regression with the variables explored in this study leads to a plausible
369 model for afforestation:

$$370 \text{ Affor} = 0.02 \text{ Roads} + 0.01 \text{ Subsidies} + 0.02 \text{ Industry} - 0.7 \text{ Forest} - 0.3 \text{ Population} - 1.2 \quad (2)$$

371 (see Table 2 for details). A similar equation which also performed well included the
372 terms roads, subsidies, population and poverty (% population below poverty line; $r^2 =$
373 61% , $n = 57$). The number of treaties signed was considered, but when included in a
374 model was generally not significant (i.e., $P > 0.05$) and was never positive, adding weight
375 to the argument that treaties are ineffective. Partial correlations indicate the performance
376 of a model by revealing any residual trends not accommodated and highlighting
377 variables which may have been omitted. Table 1 reveals that none of the partial
378 residuals resulting from Equation 2 are significant, confirming that Equation 2 is a
379 sufficient model. The adequacy of Equation 2 is demonstrated by the probabilities
380 reported in Table 2, and by an F-test assessing overall model performance ($F_{5,68} = 18.9$,
381 $P < 0.0001$).

382 **[Table 2 near here]**

383 Equation 2 should be interpreted cautiously. It is descriptive, not predictive, and thus
384 one should not conclude that paving more roads will help to save forest. Equation 2
385 does not predict future afforestation patterns, but helps to explain the patterns that were
386 observed during 1990-2000. It could be used to infer likely afforestation rates for a
387 nation not surveyed in FRA 2000, provided that the nation was representative of those
388 in FRA 2000 (e.g., that it did not have extraordinary soil fertility, a benevolent dictator,
389 etc).

390 Equation 2 includes *roads*, *subsidies*, *industry*, *forest* and *population*. Some of these
391 variables are consistent with those in other studies (e.g., *forest* and *population* in

392 Mahapatra and Kant 2005; subsidies in Fredj *et al* 2004), but the *roads* variable has a
393 different sign, suggesting that it should be interpreted broadly. For instance, it is likely
394 that in equation 2, the variable *roads* reflects the general ability of a nation to provide
395 and maintain government services, rather than the relative amount of paved and
396 unpaved road *per se*. Similarly, *industry* is likely to reflect employment opportunities
397 other than primary agriculture and timber-getting. Even population, which appears
398 straight forward, is unlikely to represent a causal relationship, and probably reflects the
399 fact that it is profitable to convert fertile lands (which support high populations) to
400 agriculture, whereas infertile and remote lands remain forested and sparsely populated.
401 Hence one should not assume that condoms and concrete can save the forests.

402 A better understanding of Equation 2 is gained by recognizing that each of the five
403 variables can be interpreted more broadly. The proportion of paved roads is just one
404 easy-to-measure indicator of good governance, and it is good governance that fosters
405 wise land use decisions (which of course, need not preclude the judicious conversion of
406 forest to agriculture where it is in the national interest). Subsidies may act directly to
407 foster afforestation, but may also reflect governments that have made considered
408 strategic decisions to foster particular activities, and which have also created deliberate
409 land-use policies. Value-adding by industry is likely to reflect employment (and small-
410 business) opportunities that are attractive alternatives to timber-getting and primary
411 agriculture (and hence forest clearance).

412 On its own, relative forest area has a weak correlation with afforestation ($r = -10\%$,
413 $P=0.09$), but its partial correlation increases substantially when used in conjunction with
414 other variables (Table 2). When considered on its own, the correlation with relative
415 forest area suggests that nations will tend towards 29% forest. This probably reflects the
416 attitude common in many frontier areas that there is plenty of forest and too little
417 agricultural land. The 29% equilibrium-point will depend on the other variables in Table
418 2, but may also be influenced by changing this attitude, through education of both
419 politicians and the populace about the environmental services provided by forests. Such
420 education has been found to enhance the effectiveness of conservation parks (Vanclay
421 2001). Curiously, this 29% equilibrium point is close to that observed in empirical
422 studies in Costa Rica (Kleinn *et al* 2002). However, the inference from Table 2 (with
423 the mean values of other variables) is that nations will tend towards no forest, unless the
424 other variables vary (i.e., roads/governance, subsidies/strategies, industry/alternatives)
425 from their overall mean. An analysis of Table 2 indicates that a 13% improvement in
426 these three variables could be sufficient to stabilize forest areas. While this estimate of
427 13% should not be taken literally, it does suggest that the task is not insurmountable.

428 In Table 2, the probabilities (P) indicate the certainty that the effect exists, and the
429 elasticity indicates the nature of the change in response to a unit change in the variable.
430 An ever-diminishing area of forest has little effect on deforestation trends (elasticity =
431 -0.14), but relatively small change in governance (*viz.* *roads*) has a relatively large
432 influence (elasticity = 0.53). Thus the elasticities reported in Table 2 suggest possible
433 priorities for development assistance, with good governance deserving top priority.

434 **Correlation or co-incidence?**

435 In an analysis of this kind where many relationships are explored, there is always the
436 danger that the selected relationships may arise simply due to chance variation. For
437 instance, if we compare the afforestation data with twenty sets of random numbers, we
438 expect that one of the sets of random numbers will show a correlation with a statistical
439 significance of $P \leq 0.05$. I have tried to minimize that danger by avoiding an exhaustive
440 analysis of all possible combinations; instead targeting indicators selected to shed light
441 on the hypotheses stated earlier (halting deforestation requires profitable alternatives
442 and services such as health, education and transport). Nonetheless, it is useful to
443 construct a test to examine the likelihood that these findings are due to chance. Chance
444 findings should exhibit probabilities that are randomly distributed between zero and
445 one, so the ranked probabilities will tend to fall in a straight line. Selective reporting of
446 chance probabilities would lead to ranked probabilities that form a straight line between
447 zero and the threshold probability level (e.g., 0.5), whereas substantive findings are
448 likely to depart from such a trend. Figure 18 illustrates the ranked probabilities reported
449 in this study. The cumulative distribution departs significantly from a straight line,
450 offering reassurance that the reported results are not merely due to chance. Another test
451 is to observe that 36 instances of $P \leq 0.001$ have been reported. If these were due to
452 solely to chance, they would represent a censored sample from 36,000 statistical tests
453 (in fact, a total of some 300 statistical tests were made). While it is impossible to rule
454 out the possibility that some individual correlations are entirely due to chance, it is
455 likely that the overall findings are reasonable, given the nature of the underlying data.

456 **[Figure 18 near here]**

457 **CONCLUSION**

458 Deforestation patterns are complex and diverse, and it is unreasonable to expect that a
459 single variable should offer a unique insight into the various mechanisms at work.
460 Nonetheless, the figures presented here offer some thought-provoking trends that may
461 help to stimulate discussion and provoke further research. This paper was precipitated
462 by a discussion about the utility of a global convention on forests. Given the nature of
463 deforestation, it is not surprising that there is no evidence that existing environmental
464 treaties have been effective in halting deforestation. It is unclear what this means for a
465 global convention on forests, but it is tempting to conclude that such a convention will
466 only be effective if it is supported by other measures (such as payments for
467 environmental services, e.g., Wunder 2005). The evidence regarding the efficacy of
468 development assistance in reducing deforestation is equivocal, so it is clear that
469 international and bilateral efforts to halt deforestation will need to be carefully targeted.
470 The FRA 2000 data offer some indications that deforestation may be halted through
471 efforts to foster good governance, encourage education and provide opportunities for
472 employment. The FRA 2000 data also suggest that subsidies may be effective and these
473 and other payments for environmental services warrant further examination.

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476 improved the manuscript.

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560 **Table 1.** Correlation between selected indicators and afforestation (square-root of % change in
561 forest area), ranked by significance (P) of the correlation for tropical nations. Indicators that are
562 consistently contrary to the expected trend are shown in **bold**.

Indicator	Units	Years	Tropical (<25°)			Global			Partials ⁷		
			R	n	P	R	n	P	r	n	P
Rural population ¹	% of population	1999	-40%	109	<.0001	-45%	181	<.0001	-3%	74	0.4
Life expectancy ²	years (at birth)	2004	40%	108	<.0001	46%	180	<.0001	7%	74	0.3
Gross domestic savings ⁴	%GDP	1990-99	46%	58	0.0001	37%	128	<.0001	-5%	71	0.3
Gross domestic product ²	Log ₁₀ (US\$/capita)	1999	34%	108	0.0002	41%	180	<.0001	1%	74	0.5
Infant mortality ²	Log ₁₀ (deaths/1000 live births)	2004	-33%	108	0.0002	-41%	180	<.0001	-3%	74	0.4
Adult illiteracy ²	Log ₁₀ (% unable to read/write)	1997	30%	106	0.0009	42%	176	<.0001	0%	74	0.5
Internet access ²	Log ₁₀ (% using internet)	2000	29%	104	0.001	40%	175	<.0001	2%	74	0.4
Credit rating ⁴	% institutional investor	2000	38%	53	0.002	46%	120	<.0001	-6%	70	0.3
CO ² emissions ⁴	Log ₁₀ (tons/capita)	1990	36%	57	0.003	52%	126	<.0001	-6%	69	0.3
International reserves ⁴	Log ₁₀ (US\$ million)	1990	33%	59	0.005	22	127	0.006	-12%	74	0.2
Commercial services ⁴	Log ₁₀ (US\$ million)	1990-98	33%	59	0.005	31%	111	0.0005	-3%	73	0.4
Agricultural value-adding ⁴	% of GDP	1990-99	-33%	60	0.005	-42%	114	<.0001	2%	74	0.4
Electricity consumption ⁴	Log ₁₀ (Kwh/capita)	1990-97	38%	41	0.007	34%	109	0.0001	5%	62	0.3
Poverty ²	% below poverty line	2000	-27%	69	0.01	-42%	111	<.0001	-9%	55	0.3
Agricultural productivity ⁴	Log ₁₀ (\$ value added/worker)	1996-98	31%	56	0.01	31%	112	0.0004	-1%	64	0.5
Environmental treaties⁵	count (0-10) ⁶	2000	-22%	94	0.02	-1%	166	0.4	-18%	74	0.06
Daily newspapers ⁴	Log ₁₀ (Papers/1000 people)	1996	29%	52	0.02	46%	125	<.0001	3%	68	0.4
Rural poverty ⁴	% below poverty line	1993	-36%	30	0.03	-46%	48	0.0005	-6%	30	0.4
Industrial value-adding ⁴	% of GDP	1990-99	24%	60	0.03	42%	113	0.0004	*		
Paved roads ⁴	% by distance	1990	24%	55	0.05	68%	123	<.0001	*		
Foreign direct investment ⁴	Log ₁₀ (US\$ million)	1990-98	22%	54	0.05	15%	124	0.05	-2%	71	0.4
Corruption index ³	0=corrupt - 10=honest	2003	22%	56	0.05	38%	120	<.0001	-1%	68	0.5
State industries ⁴	Log(%GDP value-added)	1990-97	16%	29	0.06	9%	42	0.3	23%	25	0.3
Population growth ⁴	%/year	1990-99	-15%	108	0.06	-37%	180	<.0001	-10%	73	0.1
Inflation rate ²	%/year	2002	-15%	102	0.07	-3%	172	0.4	-1%	74	0.5
Subsidies ⁴	% of total expenditure	1990-97	21%	38	0.1	53%	92	<.0001	*		
Wealth distribution ²	Gini coefficient	1995	-14%	110	0.2	-53%	104	<.0001	-3%	63	0.4
Access to clean water ⁴	% of population	1990-96	11%	58	0.2	46%	100	<.0001	-11%	52	0.2
Unemployment ²	% of population	2001	-10%	72	0.2	-27%	139	0.0006	-9%	65	0.3
Education ⁴	years of schooling	1997	14%	23	0.3	56%	69	<.0001	-16%	43	0.2
Forest area	%	2000	8%	110	0.2	-10%	182	0.09	*		
Population density ¹	Log ₁₀ (people/km2)	1999	1%	110	0.5	3%	182	0.7	*		

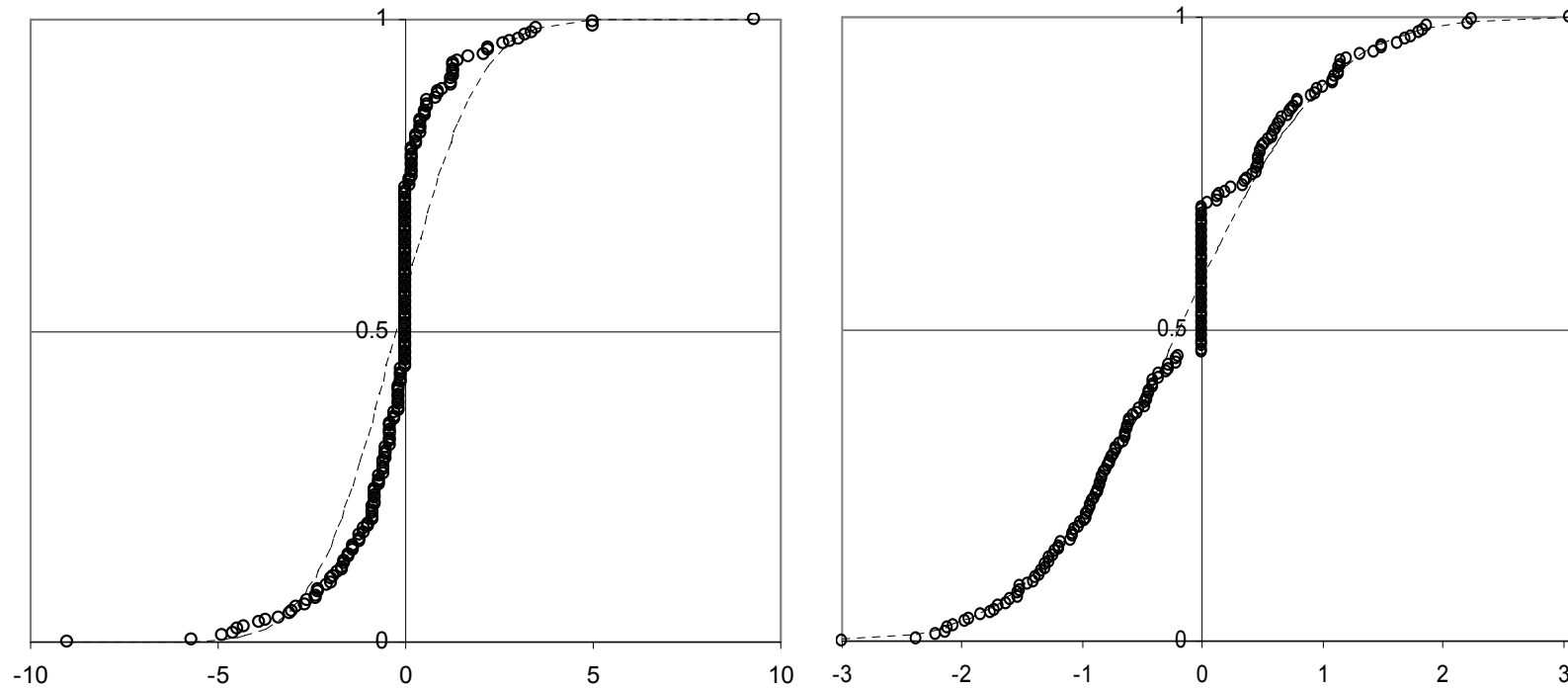
563 1. FRA 2000;
564 2. CIA 2004;
565 3. Transparency International 2003.
566 4. World Bank 2000.
567 5. ENTRI 2004.
568 6. Score 1 for party to ($\frac{1}{2}$ for signing but not ratifying) each of the following treaties:
569 Convention on Wetlands of International Importance especially as Waterfowl Habitat (Ramsar,
570 1971); Convention concerning the Protection of the World Cultural and Natural Heritage
571 (1972); Convention on the International Trade in Endangered Species of Wild Flora and Fauna
572 (CITES, 1973); International Tropical Timber Agreement (1983); Montreal Protocol on
573 Substances that Deplete the Ozone Layer (1987); *Convention on Biological Diversity* (1992);
574 United Nations Framework Convention on Climate Change (1992); International Tropical
575 Timber Agreement (1994); *United Nations Convention to Combat Desertification in those*
576 *Countries experiencing Serious Drought and/or Desertification, particularly in Africa* (1994);
577 *Kyoto Protocol to the United Nations Framework Convention on Climate Change* (1998).
578 7. Partial correlations indicate any residual trends not explained by Equation 2; asterisks
579 indicate variables included in Equation 2.

580 **Table 2.** Parameter estimates for equation 2, based on 74 observations ($r^2 = 58\%$).

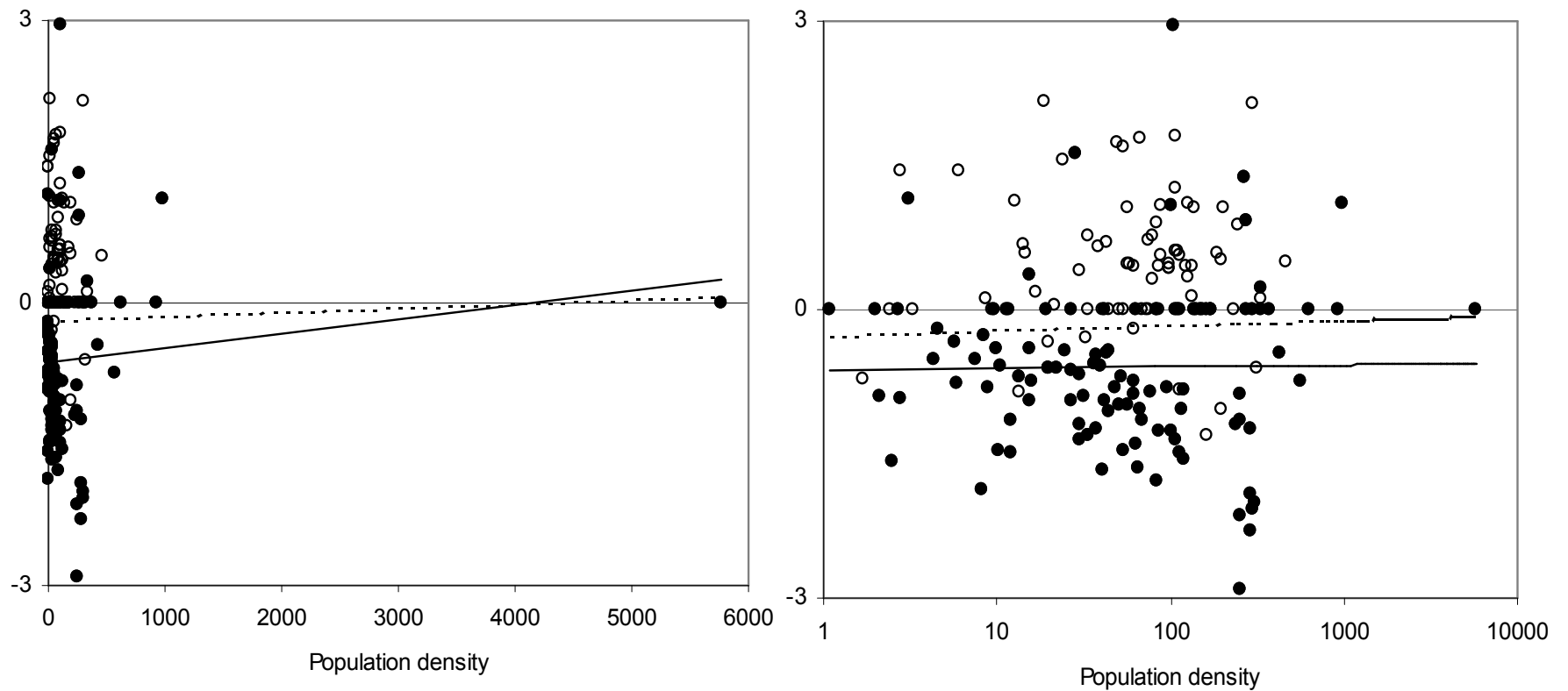
Source	Units	Estimate	s.e.	P	Elasticity
Intercept		-1.241	0.379	0.002	
Roads	% of roads paved	0.016	0.003	<.0001	0.53
Subsidies	% total government spending	0.011	0.004	0.01	0.23
Industry	% value added	0.018	0.009	0.03	0.16
Forest	% of land area in 2000	-0.699	0.382	0.04	-0.14
Population	$\text{Log}_{10}(\text{people}/\text{km}^2)$	-0.258	0.145	0.04	-0.16

581

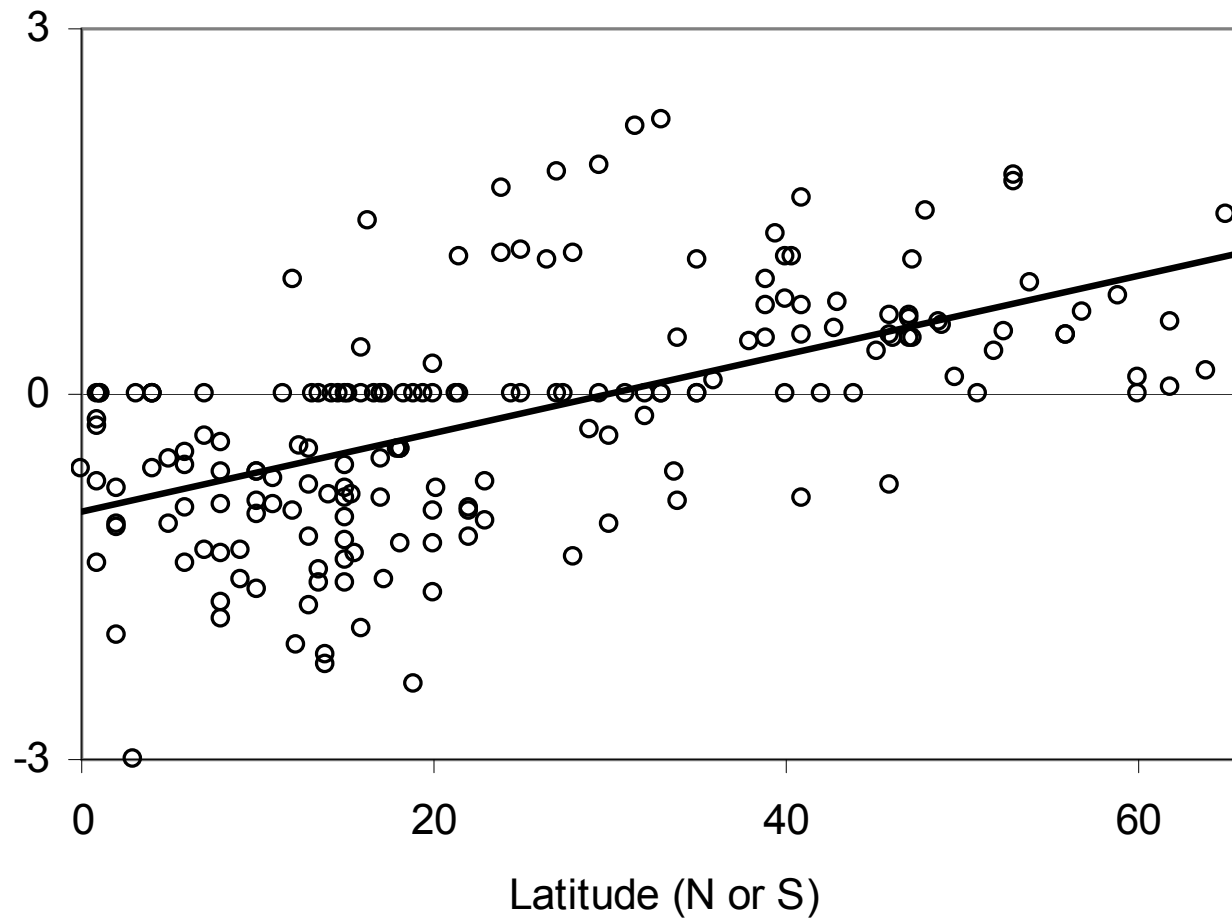
582 **Figure 1.** Cumulative distribution of forest change data (FRA 2000) before (left) and after (right) square-root transformation. Notice
583 that after transforming, the data points correspond more closely to the normal distribution (dashed line) assumed in statistical
584 analyses.



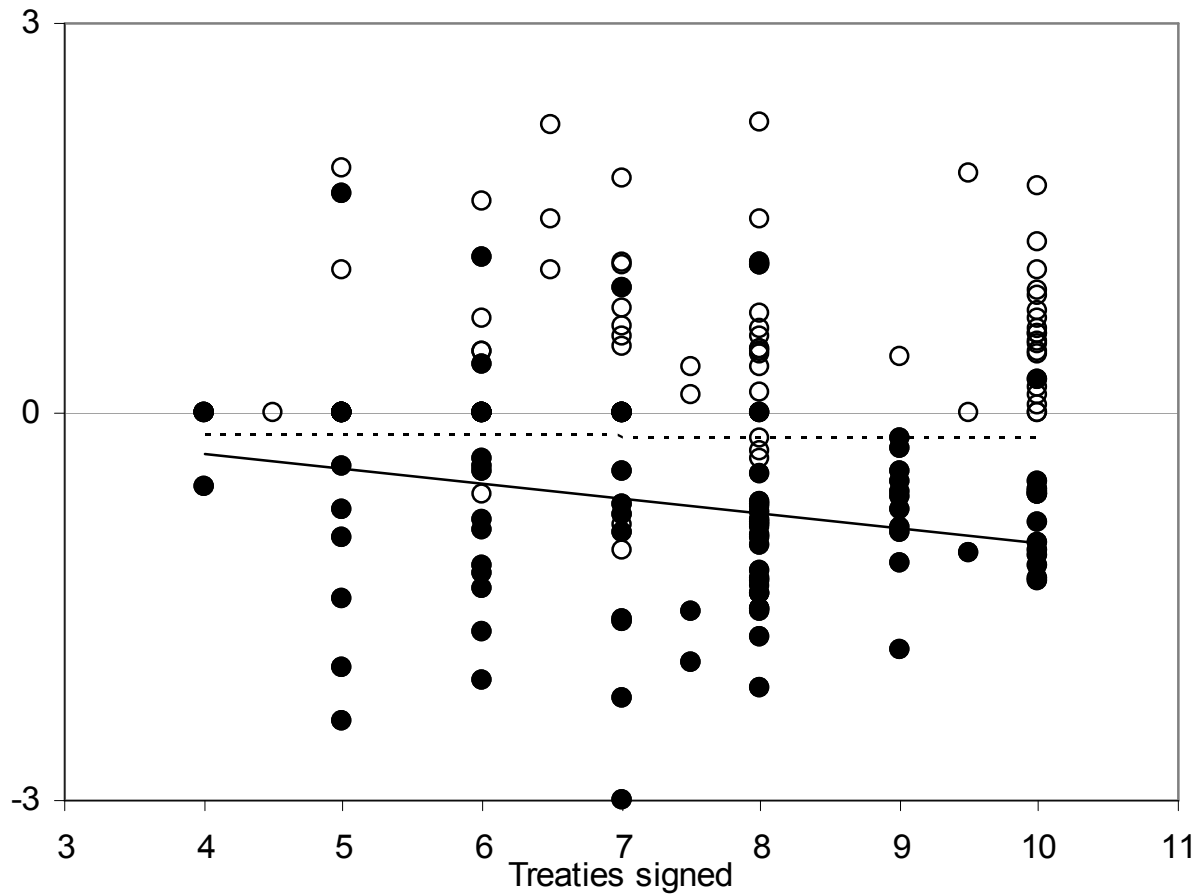
585 **Figure 2.** The effect of a logarithm transformation on population density data and its relationship with afforestation (square root of
586 change in forest area). Solid circles and solid line are tropical nations; empty circles are temperate nations, and the dotted line is the
587 global trend.



588 **Figure 3.** Afforestation (square root of change in forest area) is correlated with latitude, with most deforestation occurring in the
589 tropics ($\leq 25^\circ$ latitude).

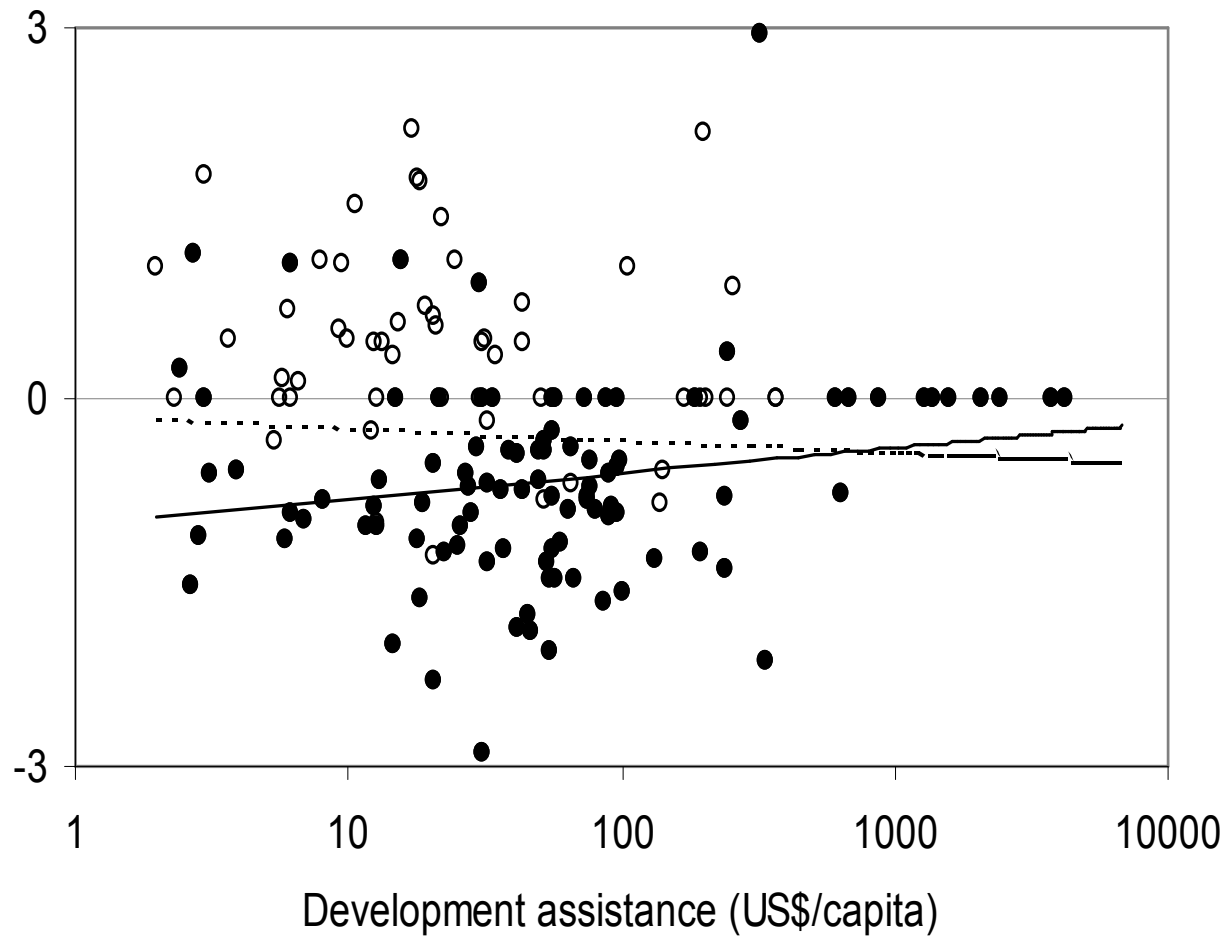


590 **Figure 4.** Participation in international treaties provides no guarantee that deforestation will cease. Solid circles and solid line are
591 tropical nations; empty circles are temperate nations, and the dotted line is the global trend. There is no evidence that treaties are
592 effective in conserving forest.

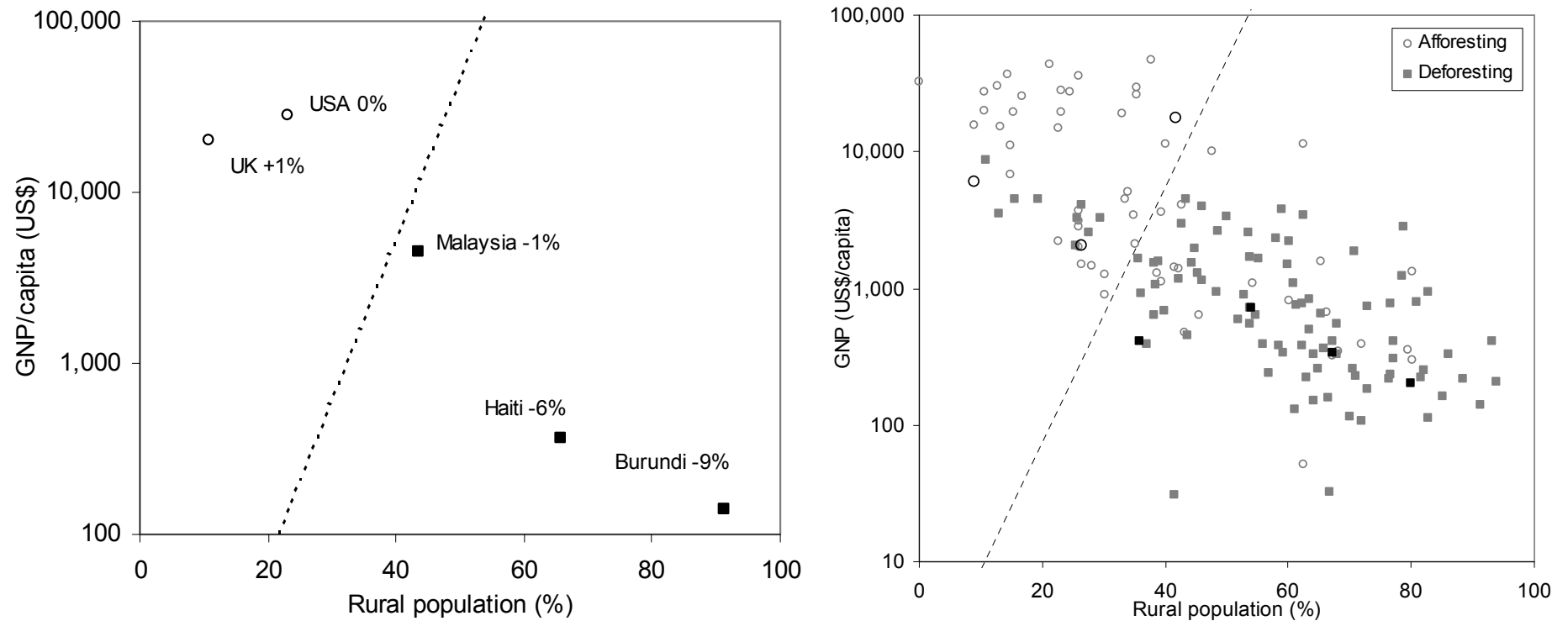


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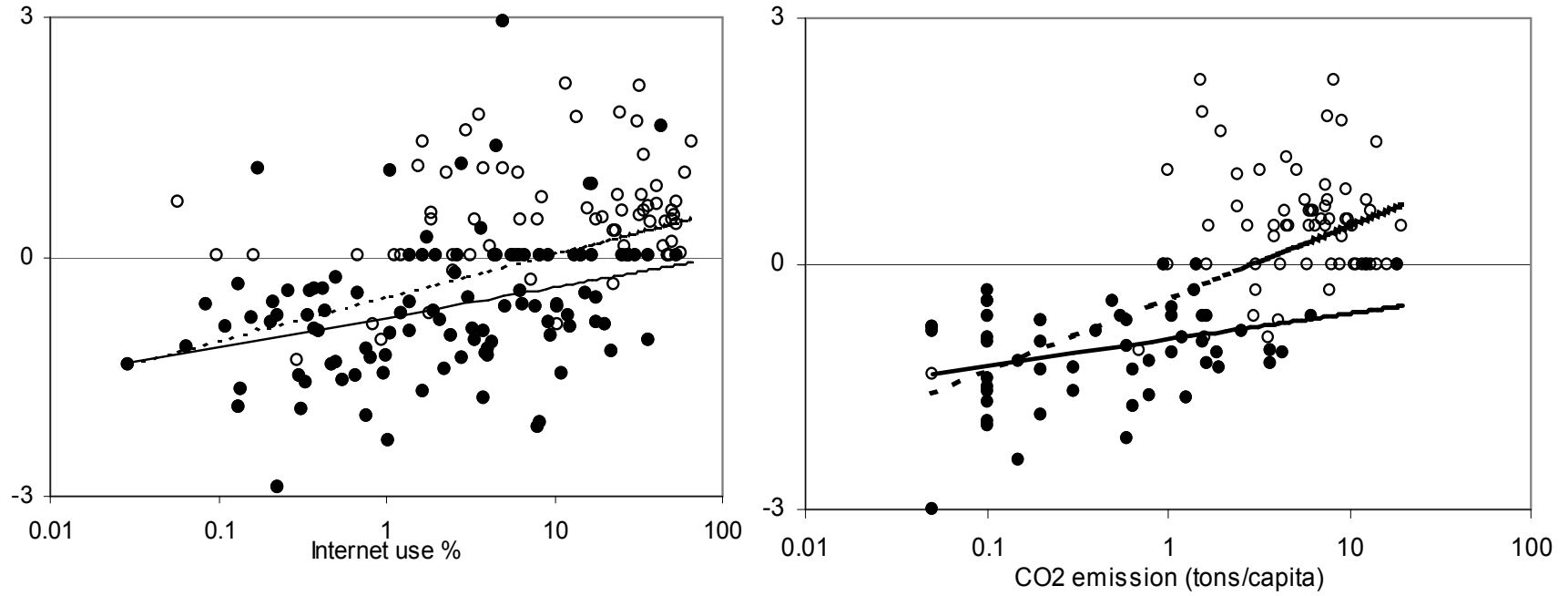
594 **Figure 5.** Development assistance and afforestation, based estimates from CIA (2004) and World Bank (2000). Filled circles and
595 solid line are tropical, empty circles are temperate nations, and the dashed line represents the global trend.



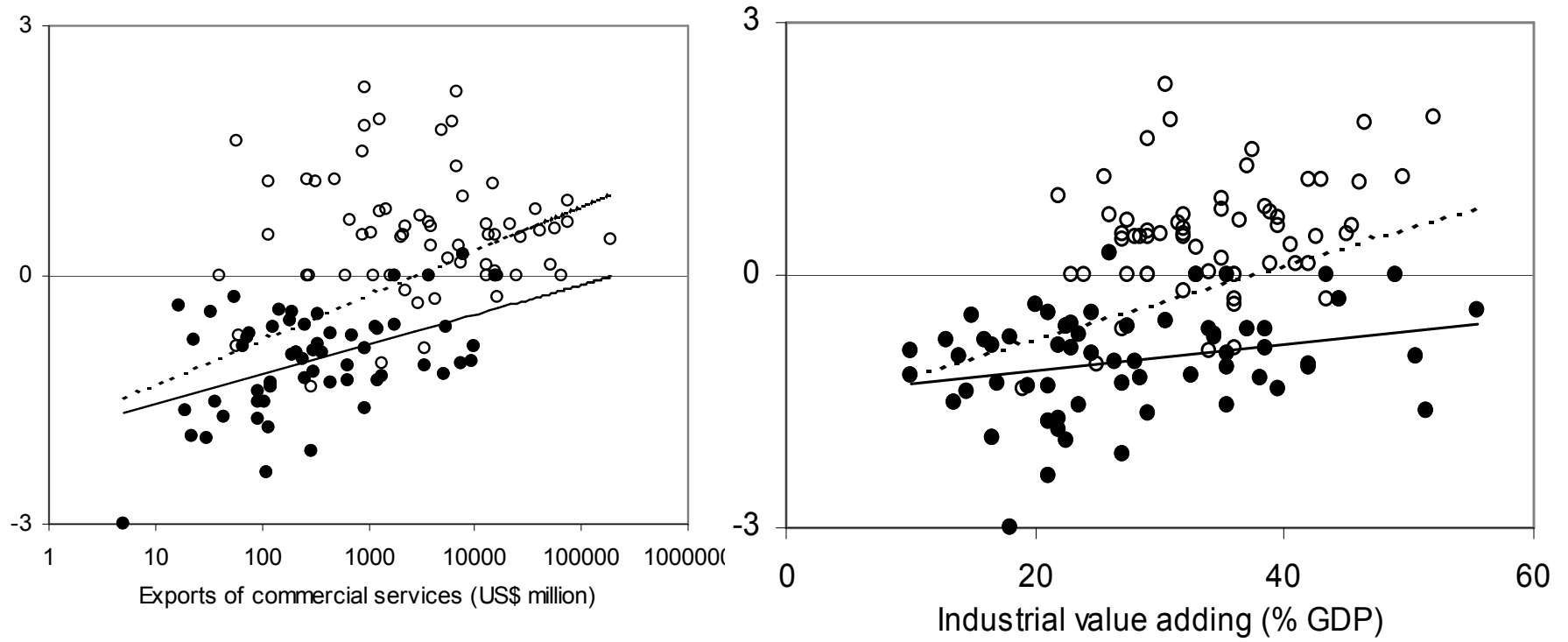
596 **Figure 6.** Propensity to afforest plotted against GNP (US\$/capita in 1997) and rural population (% in 1999) for selected countries
 597 (left) and for all FRA 2000 countries (right). Filled squares are deforesting nations, and open circles are afforesting countries. The 3
 598 large circles and 4 black squares denote countries with rates exceeding $\pm 3\%$ and 500,000 ha/year.



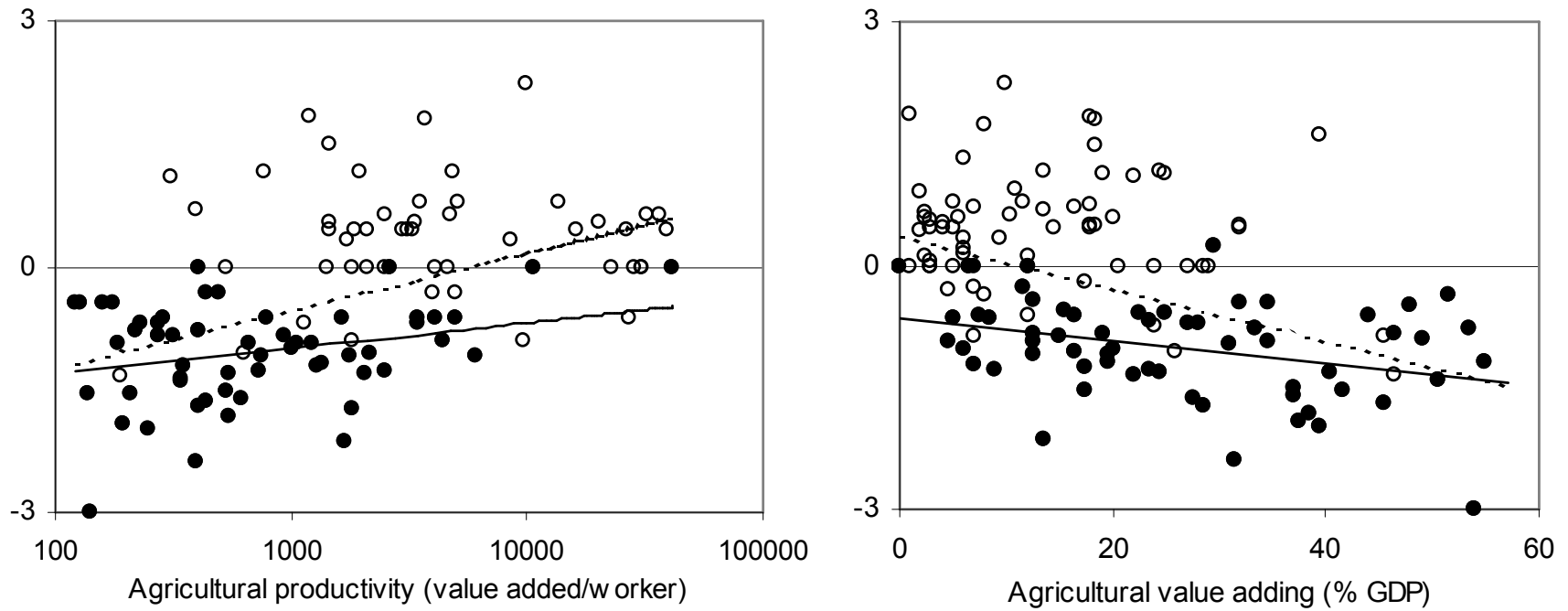
599 **Figure 7.** Indicators reflecting alternative employment and their correlation with afforestation.



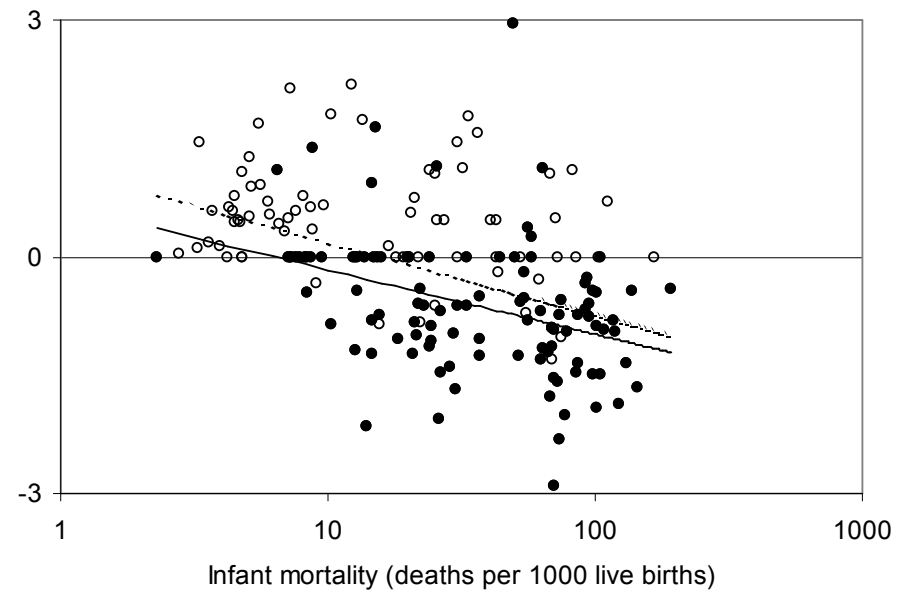
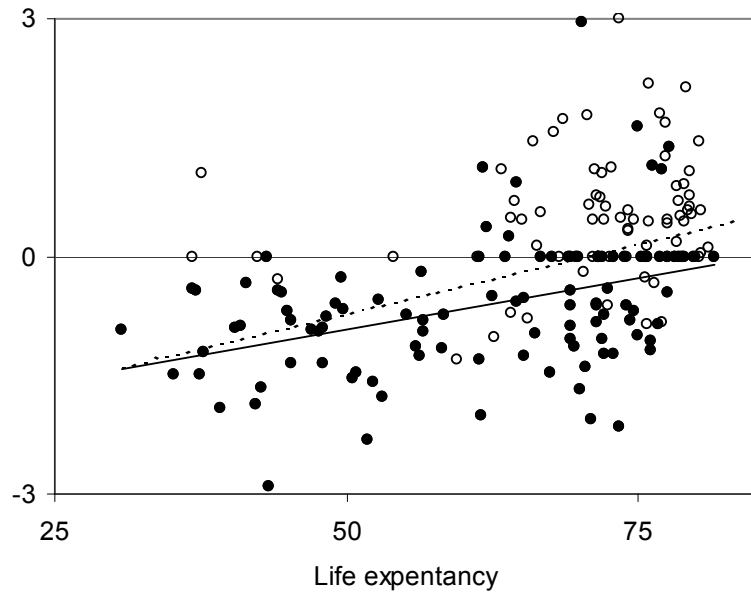
600 **Figure 8.** Increased commercial and industrial activity may lead to a reduction in deforestation.



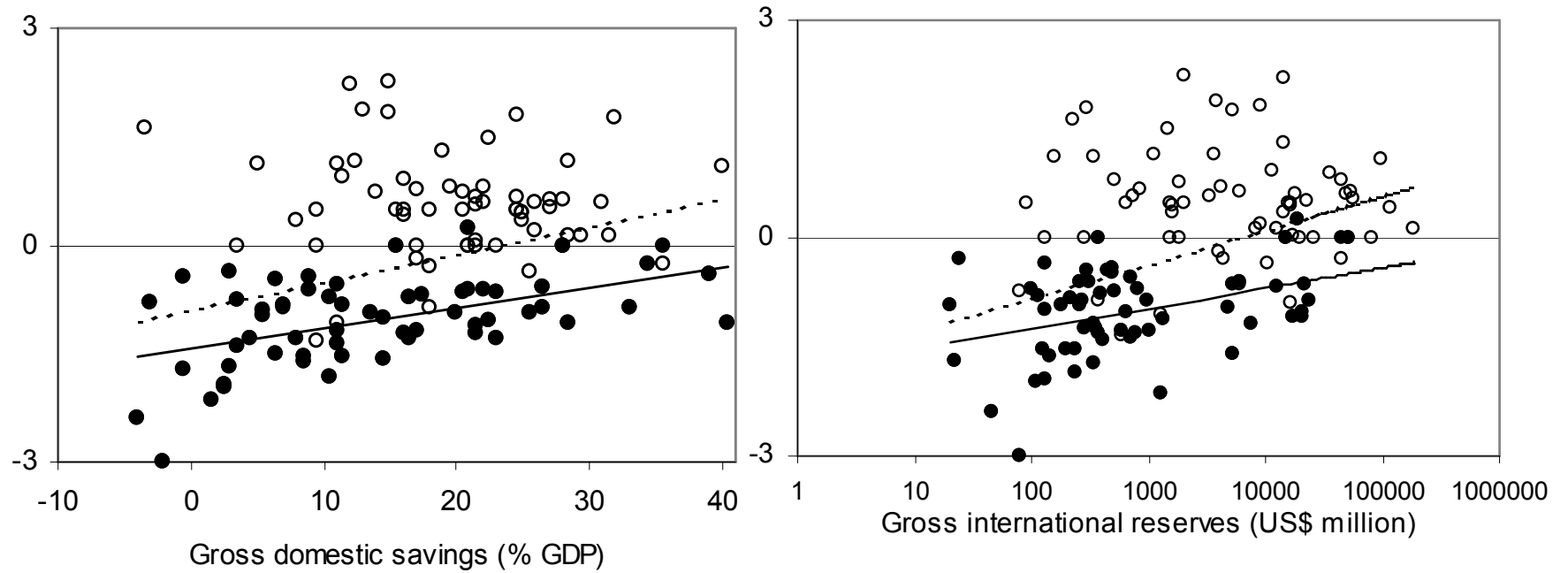
601 **Figure 9.** Afforestation is favoured by increasing the value-added per worker, but not by increasing the agricultural contribution to
602 GDP.



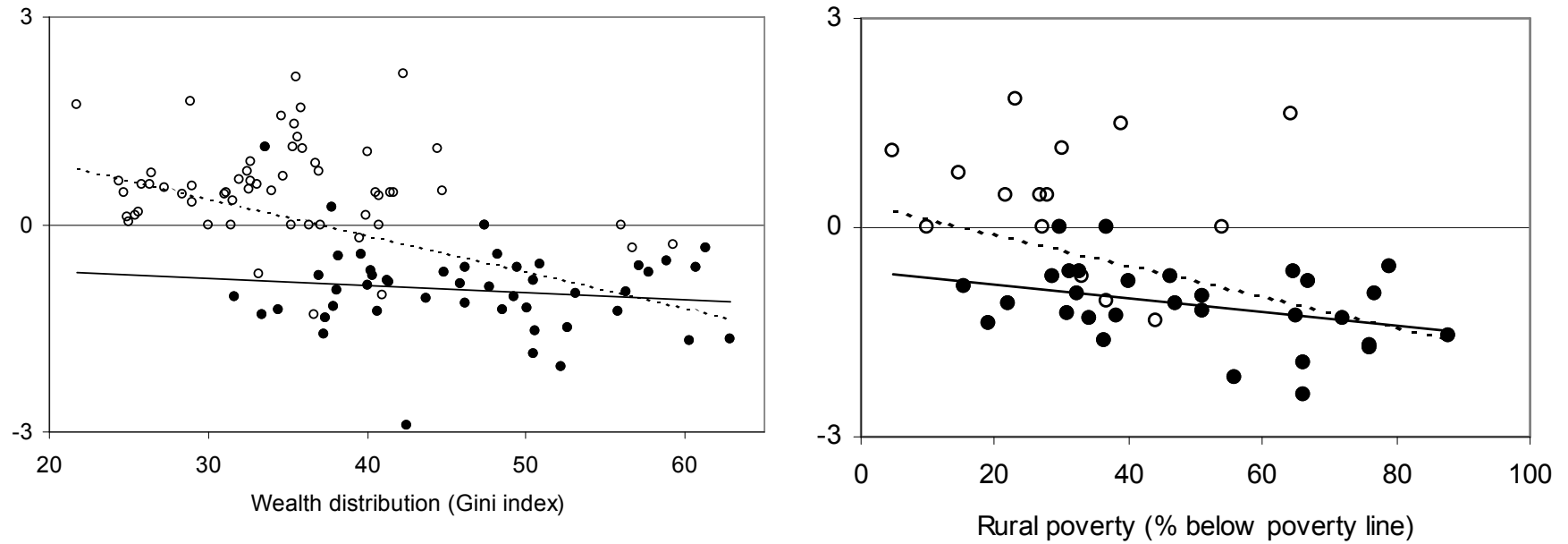
603 **Figure 10.** Health indicators and propensity to afforest. Nations with better health (longer life expectancy and fewer infant deaths)
604 tend to have less deforestation.



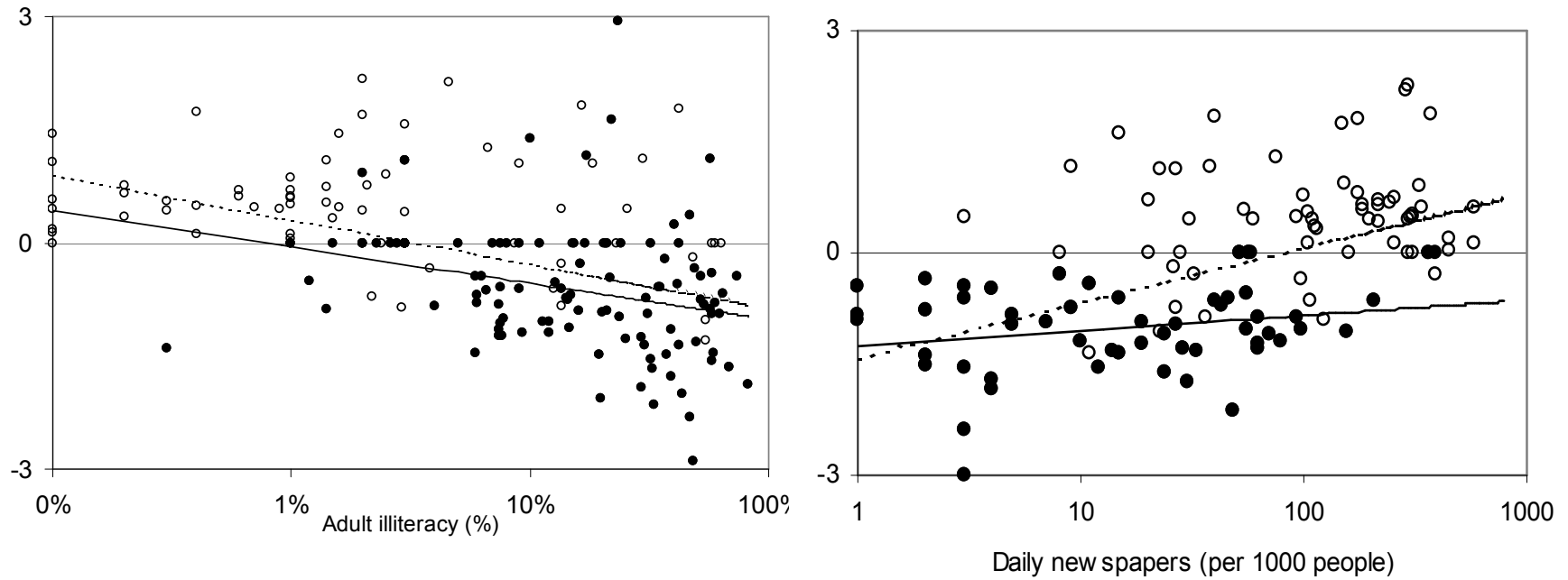
605 **Figure 11.** Afforestation tends to increase as national savings (as a % of GDP) increase, and as international reserves increase.



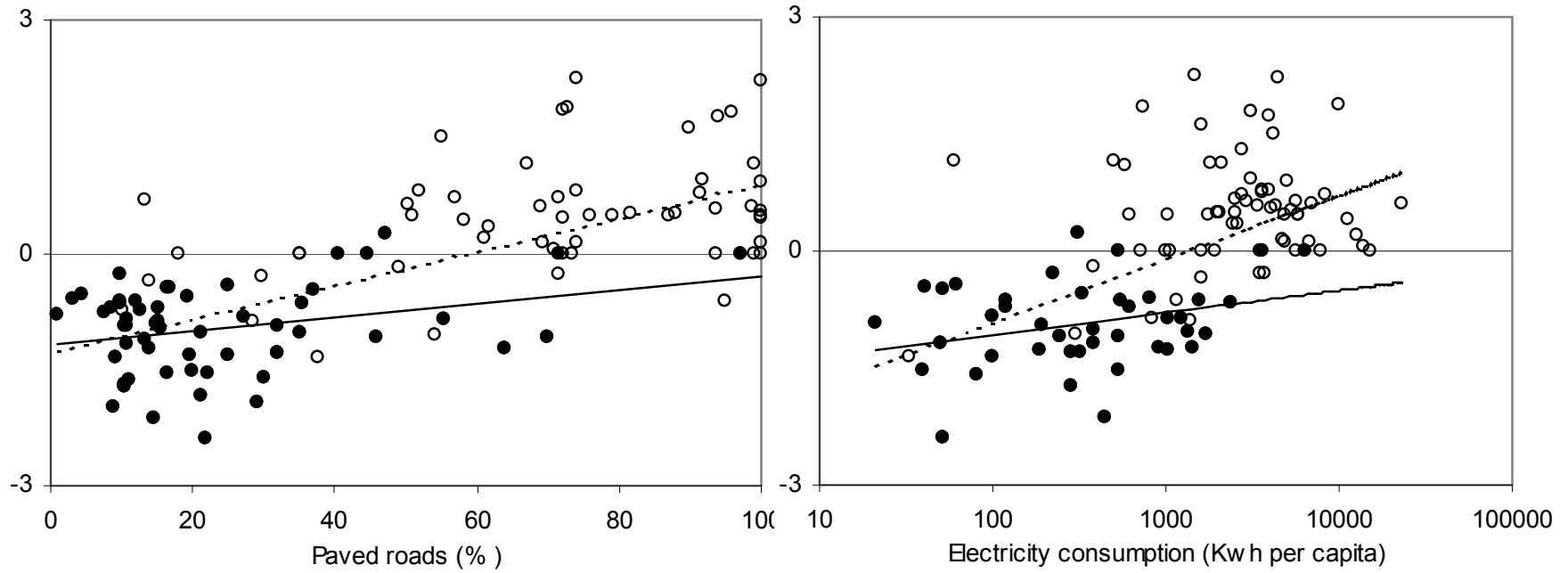
606 **Figure 12.** Afforestation may be influenced by wealth distribution (left) and rural poverty (right). Less rural poverty, and a more
607 equal distribution of wealth, favour afforestation.



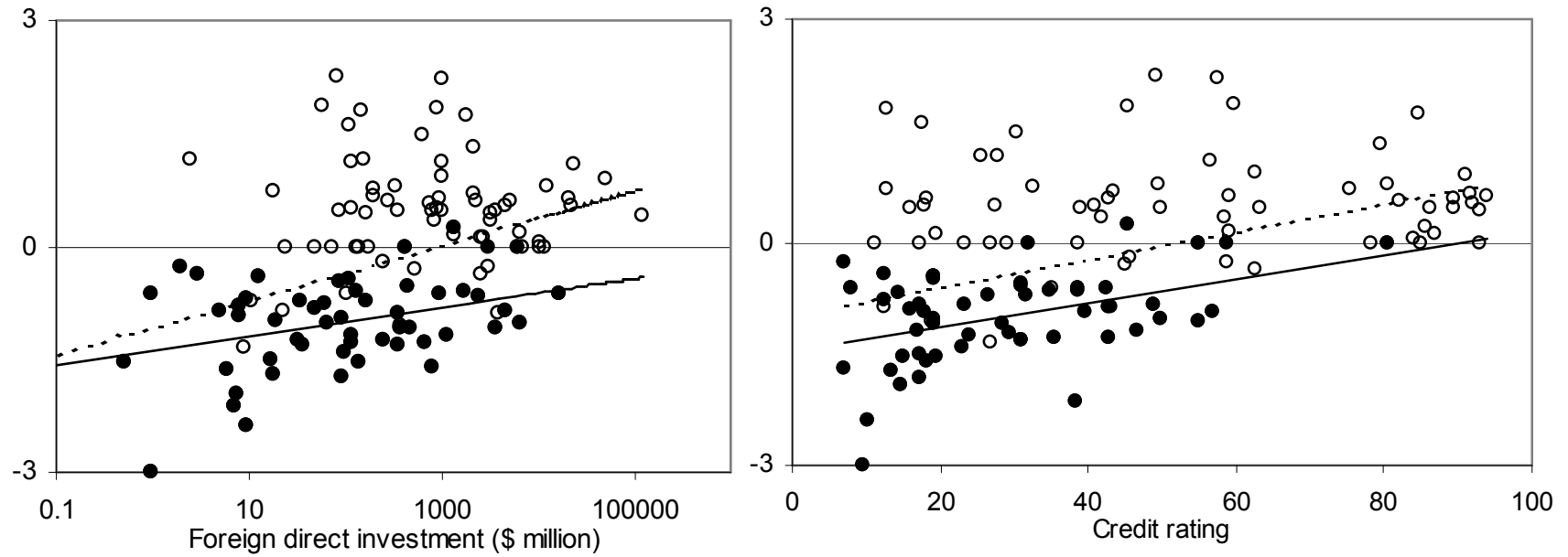
608 **Figure 13.** Making information accessible helps to halt deforestation. Left shows illiteracy, the percentage of adults over 15 unable to
609 read, on a logarithmic scale.



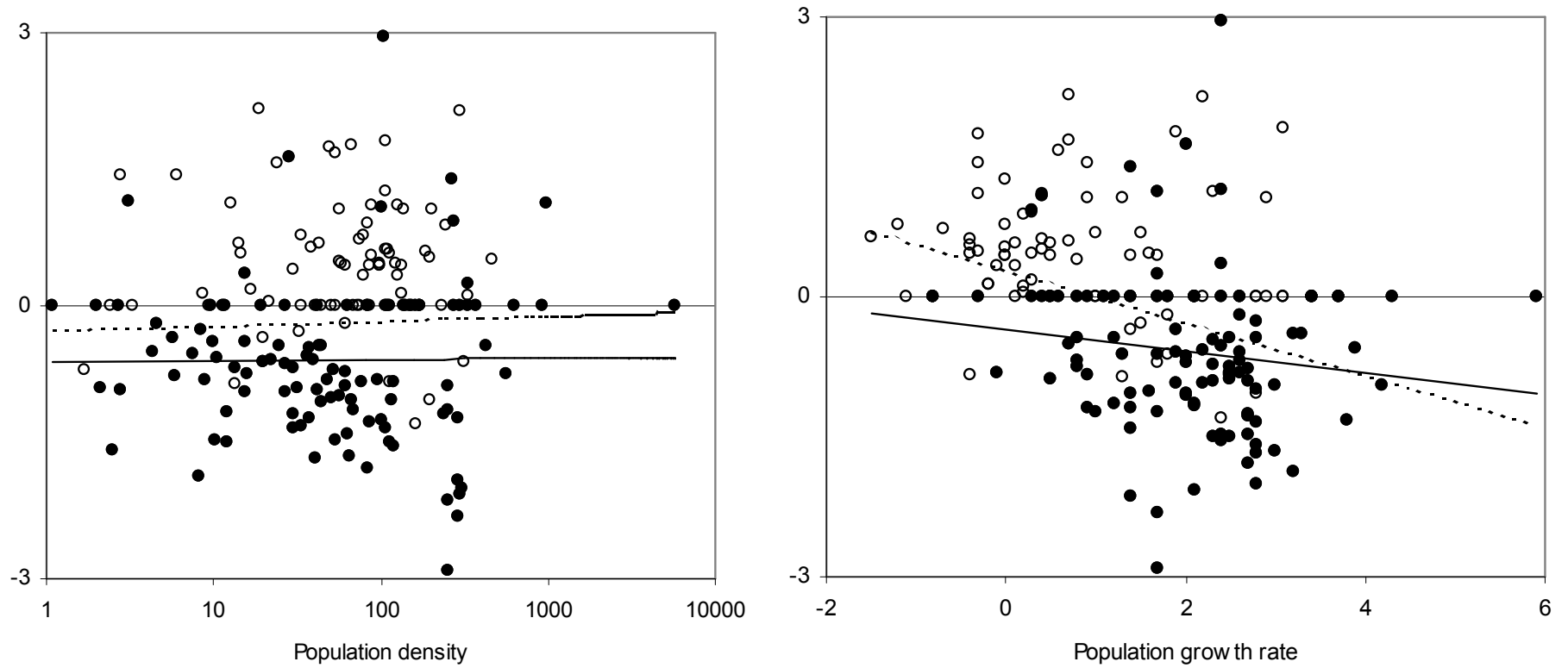
610 **Figure 14.** The provision of paved roads and of electricity are indicators of society's ability to provide and maintain services.



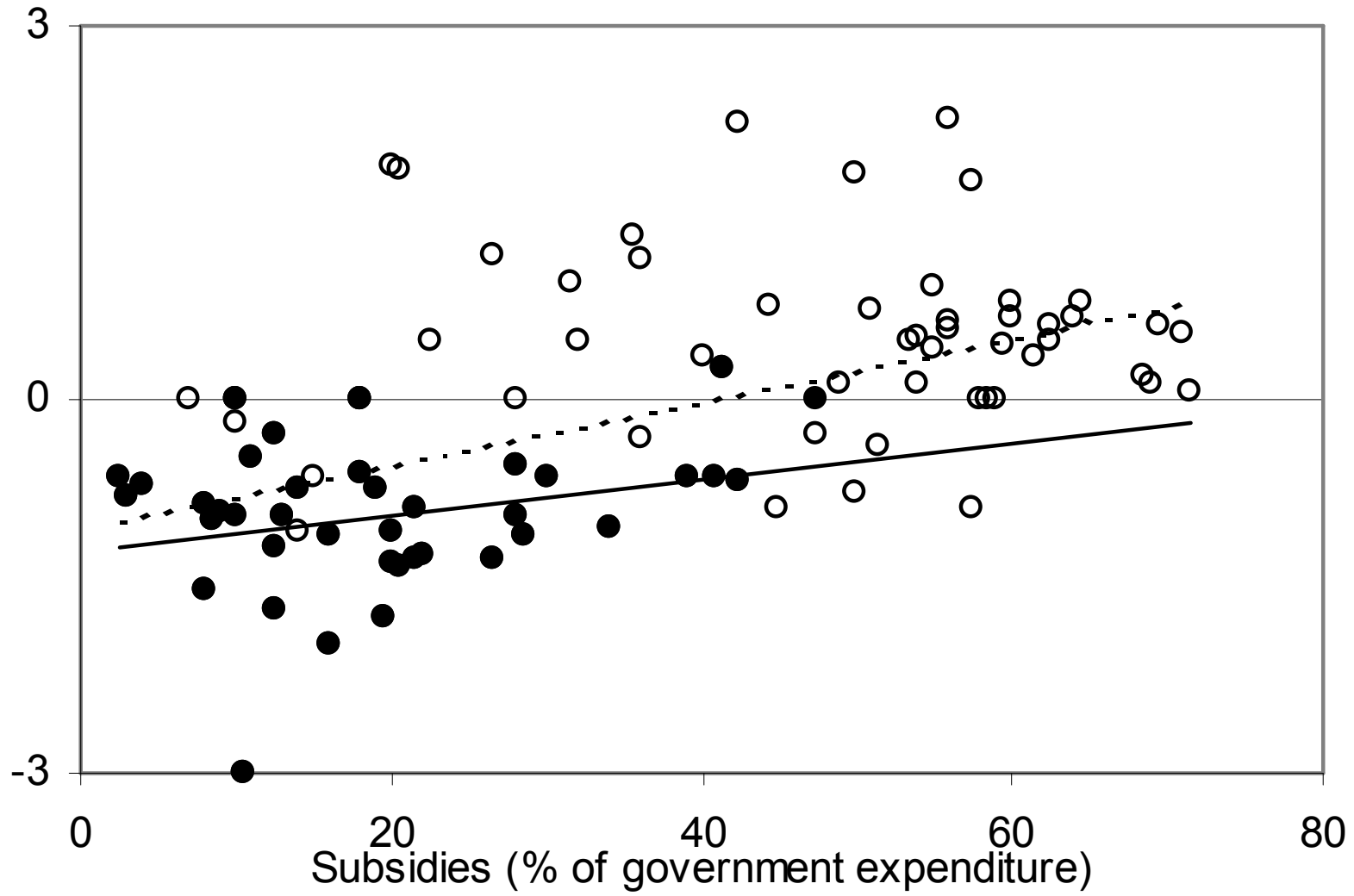
611 **Figure 15.** Confidence, reflected here as foreign investment (left) and credit rating for institutional investors (right), increases the
612 propensity to afforest.



613 **Figure 16.** The correlation between population density and afforestation is weak, whereas rapid population growth rates tend to be
614 associated with deforestation.



615 **Figure 17.** Subsidies and afforestation.



616 **Figure 18.** Ranked probabilities reported in this study are not random.
617

