Tropical countries may be willing to pay more to protect their forests

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Inadequate funding from developed countries has hampered international efforts to conserve biodiversity in tropical forests. We present two complementary research approaches that reveal a significant increase in public demand for conservation within tropical developing countries as those countries reach upper-middle-income (UMI) status. We highlight UMI tropical countries because they contain nearly four-fifths of tropical primary forests, which are rich in biodiversity and stored carbon. The first approach is a set of statistical analyses of various cross-country conservation indicators, which suggests that protective government policies have lagged behind the increase in public demand in these countries. The second approach is a case study from Malaysia, which reveals in a more integrated fashion the linkages from rising household income to increased household willingness to pay for conservation, nongovernmental organization activity, and delayed government action. Our findings suggest that domestic funding in UMI tropical countries can play a larger role in (*i*) closing the funding gap for tropical forest conservation, and (*ii*) paying for supplementary conservation actions linked to international payments for reduced greenhouse gas emissions from deforestation and forest degradation in tropical countries.

protected area | valuation | choice experiment | REDD

Primary forests—"forests of native species in which there are no clearly visible signs of past or present human activity" (ref. 1, p. 11)—are globally significant repositories of biodiversity (2) and carbon (3). The global area of these forests is declining at an annual percentage rate that is nearly triple the rate for total global forest area (ref. 1, tables 2.4 and 3.3). Virtually all of the loss is occurring in tropical countries (*SI Text*, section 1). Logging is the main cause of the loss (ref. 1, p. 27), but hunting threatens biodiversity even in primary forests with intact tree cover (4, 5).

Protecting primary tropical forests is a core mission of several international institutions created since the early 1990s, including the Convention on Biological Diversity (CBD), the Global Environment Facility (GEF), and the UN Collaborative Program on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD). However, the CBD failed to achieve its goal of significantly reducing biodiversity loss by 2010 (6); international funding for biodiversity protection through the GEF and other mechanisms is below commitments made at the 1992 Earth Summit (7) and the amounts required to achieve the CBD's 2020 protection targets (8); and REDD has not advanced beyond a readiness phase (www.un-redd.org). Relying on international mechanisms to fund protection of primary tropical forests does not look like a winning strategy.

Here, we argue that economic development during the past 20–25 y has raised public demand for forest protection within tropical countries, but the level of protection supplied by tropical country governments has not kept pace. We focus on the dynamics of conservation and development within relatively wealthier developing countries: The group that is classified by the World Bank as upper-middle income (UMI). As we will show, the majority of primary forest area in tropical countries is found in these countries. We hypothesize that public willingness to pay (WTP) to protect forests has reached a relatively high level in UMI countries, leading to greater support for local conservation nongovernmental organizations (NGOs) and prompting governments to boost forest protection efforts—but not as much as the public would like. This gap between domestic demand and domestic supply of forest protection has two important implications: Domestic funding might be sufficient to cover the costs of additional protection in some, and perhaps many, tropical countries; and international funding might be able to leverage more domestic funding than it currently does.

Although many cross-country studies in the environmental Kuznets curve (EKC) literature have investigated the effect of rising national income on deforestation (9), none has considered the effect on primary forests. This gap matters because deforestation, unlike primary forest loss, results mainly from agricultural conversion, not logging (1, 10). A few cross-country studies have considered the effect of national income on creation of protected areas (11–16), but with mixed findings on the significance of the effect. A second and larger group of studies has used surveys to measure WTP for biodiversity conservation by domestic populations within particular countries. Most of these studies have failed to detect a significant income effect ($P < 0.05$) (17, 18). Metaanalyses of these studies estimate income effects that are generally positive (protection increases with income) but not necessarily statistically significant (17, 18).

We extended this prior work by coupling two research approaches: a broad-brush statistical analysis of the association between a standard measure of economic development, i.e.,

Significance

Tropical forests, especially the primary tropical forests that are globally important for biodiversity conservation and carbon storage, are increasingly concentrated in relatively wealthier developing countries. This creates an opportunity for domestic funding by these countries to play a larger role in (*i*) closing the funding gap for tropical forest conservation, and (*ii*) paying for supplementary conservation actions linked to international payments for reduced greenhouse gas emissions from deforestation and forest degradation.

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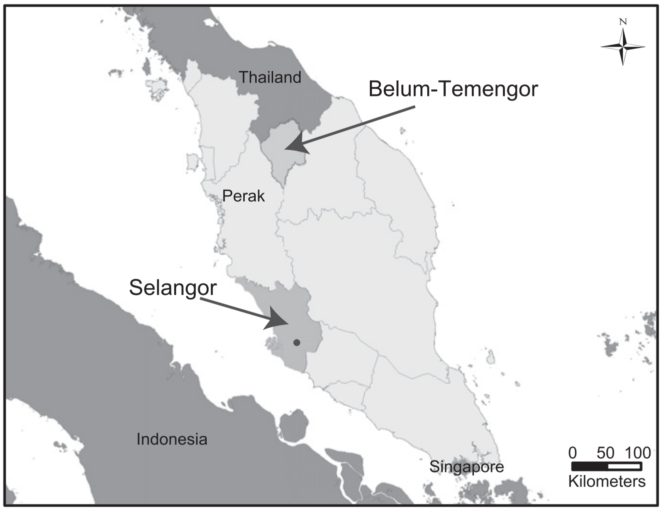

Fig. 1. Locations of Belum–Temengor (site of forest protection plans in choice experiments) and Selangor and Kuala Lumpur (site of household survey; the black dot is Kuala Lumpur) within Peninsular Malaysia (light gray). Lines show Malaysian state boundaries. Sources: base map, GADM database (www.gadm.org); Belum–Temengor boundaries, Forest Research Institute Malaysia.

per capita gross national income (GNI), and a large set of cross-country conservation indicators (CIs); and a focused investigation of forest protection in a particular UMI country, Malaysia. The statistical analysis spanned 12 indicators from 10 diverse sources (*Materials and Methods* and *SI Text*, section 1). The indicators pertained to public environmental preferences, conservation NGOs, and government action (conservation spending, protected area establishment). These indicators relate more directly to our hypothesis about domestic demand and domestic supply of forest protection than do the deforestation rates analyzed by EKC studies. We limited the samples to countries classified as tropical by the UN Food and Agriculture Organization Forestry Department (ref. 19, data table 2) and paid special attention to differences between tropical countries in the UMI group and ones in lower income groups.

The Malaysian case study allowed us to examine more closely the linkages from rising household income to increased household WTP, NGO engagement, and government protective action, and thereby uncover reasons for the underprovision of forest protection relative to household preferences. The case concerned Belum–Temengor, a 300,000-ha forested region in the state of Perak (Fig. 1). This region contains the largest area of primary forest in Peninsular Malaysia outside a national park. Our research included a population-representative survey of 1,261 rural and urban households in the Malaysian state of Selangor and the federal territory of Kuala Lumpur during 2010 (*Materials and Methods*). We used choice experiments (20, 21) to estimate household WTP to protect Belum–Temengor against logging and poaching (*SI Text*, section 2). Information from the case study enabled us to compare the public's aggregate WTP for protection to current protection expenditures and to discuss why there is a gap between the two.

Results

Forests in UMI Tropical Countries. By 2010, nearly half of the global area of forests in tropical countries was in 27 countries classified by the World Bank as UMI (*SI Text*, section 1). These countries included Brazil, Costa Rica, Gabon, Malaysia, Mexico, Peru, and Thailand. The UMI group is expanding: Only 9 of the 27 countries were in it in 1990, and 9 additional tropical countries will join it within 25 y (and 10 more within 50 y) if 1995–2012 income growth rates continue (*SI Text*, section 1). UMI countries also contained a disproportionate share of the 2010 global area of primary forest in tropical countries (Fig. 2). They contained nearly half of the threatened endemic mammal, bird, and plant species found in tropical countries (Fig. 2) and ranked highly according to several other biodiversity indicators (*SI Text*, section 1), including megadiversity (22), irreplaceable protected areas (23), the GEF benefits index (24), and the mammal global biodiversity fraction (25).

Cross-Country Evidence on Conservation in Tropical Countries. The most empirically compelling approach for statistically identifying associations between CIs and economic development involves analyzing changes within countries over time, by using fixed-effects regression models to control for unobserved country characteristics that could confound the observed associations. This approach requires data that vary not only cross-sectionally but also longitudinally. We compiled such data for six indicators (Table 1). We first tested the difference between an indicator's mean when countries were in the low- or lower-middle-income group and its mean when the countries were in the UMI group (central columns in Table 1). We found consistent evidence that reaching the UMI group was associated with higher public support for environmental protection (the first two indicators), larger donations to domestic conservation NGOs (the third indicator), and a stronger government response as measured by cofinancing of GEF forest biodiversity projects (the fourth indicator) and creating protected areas (the last two indicators).

To illustrate, consider the first indicator. The results indicate that, on average, the share of households that favored protecting the environment over economic growth and job creation was 0.116 higher when countries were in the UMI group than in the lower-middle-income group and 0.276 higher when they were in the UMI group than in the low-income group. Similarly, when countries were in the UMI group instead of one of the lower income groups, higher shares of households identified the environment as the most serious problem confronting their countries, domestic donations to the countries' World Wide Fund for Nature (WWF) chapters were higher, cofinancing accounted for

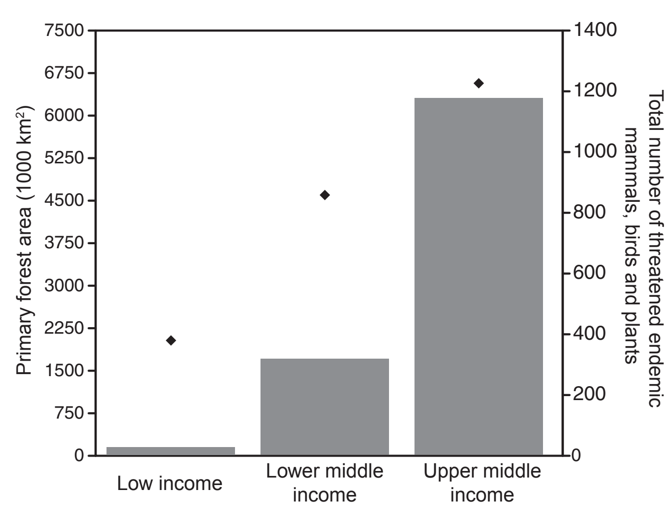

Fig. 2. Aggregate primary forest area (bars, left axis) and number of threatened endemic mammal, bird, and plant species (diamonds, right axis) in tropical countries, by World Bank income group. Area estimates and income classification are for 2010, whereas species estimates are for 2013. Estimates are not shown for high-income tropical countries, which account for very small shares of both variables. See *SI Text*, section 1 for data sources.

Table 1. **Association of economic development with cross-country CIs that have data for multiple years**

Variable	Source	Mean for indicated income group minus mean for UMI group			Per capita GNI	
		n	Low income	Lower-middle income	*n*	Elasticity
Public opinion						
1 = protecting the environment should be given priority, 0 = economic growth and creating jobs should be the top priority	World Values Survey	54,058 household years	−0.276 (0.000)	−0.116 (0.008)	50,815 household years	0.745 (0.000)
1 = environment is the most serious problem facing the country, 0 = other problems are more serious	AmericasBarometer	113,226 household years	−0.00797 (0.031)	−0.00511 (0.148)	101,039 household years	5.32 (0.005)
Domestic donations to WWF (constant 2005 US dollars per thousand people)	WWF country chapters	42 country years	−1.03 (0.084)	−0.772 (0.174)	42 country years	5.64 (0.001)
% cofinancing of GEF forest biodiversity projects	GEF	369 projects	−24.7 (0.002)	−12.0 (0.008)	324 projects	0.655 (0.002)
% land area in terrestrial protected areas	World Bank	2,285 country years	−3.18 (0.000)	−1.94 (0.009)	1,416 country years	0.311 (0.001)
% land area in forests protected for biodiversity conservation	UN Food and Agriculture Organization	361 country years	−0.758 (0.080)	−0.418 (0.260)	254 country years	0.189 (0.072)

For each indicator, results are shown for two regression models that included country fixed effects. Results for the first model (three center columns) give the difference between an indicator's mean when countries were in the low- or lower-middle-income group and its mean when countries were in the UMI group. Negative values indicate that the mean was higher when countries were in the UMI group. Results for the second model (last two columns) show the association between an indicator and per capita GNI, as a continuous measure of development level that is more precise than income group. A positive elasticity of value *x* indicates that, on average, a 1% change in per capita GNI over time in a country was associated with an *x*% increase in the indicator. *P* values for two-sided *t* tests of differences from zero are shown in parentheses next to the estimates. Samples included only tropical countries (ref. 19, data table 2). See *Materials and Methods*; *SI Text*, section 1; and Table S1 for additional details.

larger percentages of the budgets of GEF forest biodiversity projects, and protected areas and forests protected for biodiversity conservation covered larger percentages of national land area. Not surprisingly, differences were larger and more highly significant between the UMI group and the low-income group than between the UMI group and the lower-middle-income group.

We then tested the association between each indicator and country-level per capita GNI, as a continuous measure of development level that is more precise than income group. Table 1 presents these associations as elasticities: the percentage change in an indicator for a 1% increase in per capita GNI. All of the elasticities were positive, with significance levels ranging from $P < 0.001$ to $P = 0.072$. This positive effect is consistent with the income-group results. The unitless nature of elasticities enabled us to compare their relative sizes, and this comparison supports our hypothesis that emerging household preferences for protection have not translated expeditiously into official action: The indicators of public opinion and NGO donations were more responsive to increases in income than the indicators of government action. Government action has been especially slow to respond to rising income in the case of forest protection for biodiversity conservation.

Data were available for a single time period for six other CIs: public concern about global loss of biodiversity, number of environmental NGOs per million people, and four indicators of domestic spending on conservation, protected areas, and forestry. Although these purely cross-sectional indicators do not allow the use of fixed effects to control for unobserved influences as in the case of the indicators in Table 1, they do allow us to consider whether the patterns in that table hold across a wider array of evidence. We found that they do (Table S2): The indicators were higher on average for the UMI group than for the lower income groups and were positively and significantly ($P < 0.05$) associated with per capita GNI.

Malaysian Case Study: Protecting Belum–Temengor Against Logging and Poaching. Compared with the cross-country analyses, the Malaysian case study provides more tightly integrated evidence of public demand for conservation rising with economic development, local NGOs playing a lead role in advocating stronger government action to protect forests, and the government response falling short of the NGOs' goal and the public's preferred protection level. This evidence indicates that public WTP for protection far exceeds public expenditures.

Malaysia reached the UMI level in 1992. Its initial growth after independence in 1957 was fueled by conversion of lowland rainforests to rubber and oil palm plantations (26). Belum–Temengor has been spared conversion due to its hilly terrain and moderate-to-high elevation. As early as 1968 (27), a report commissioned by the Malaysian federal government recommended establishing a wildlife reserve in Belum–Temengor to protect populations of the Asian elephant, Malayan tiger, Sumatran rhinoceros, and other large mammals.

Protecting Belum–Temengor against logging and poaching has been a priority of Malaysia's two leading conservation NGOs, the Malaysian Nature Society (MNS) and WWF Malaysia, since the early 1990s (28). The Malaysian constitution assigns jurisdiction over forests to state governments (26). MNS and WWF Malaysia have used a variety of approaches to convince the Perak state government to protect Belum–Temengor (28), including organizing scientific expeditions, enlisting the support of federal agencies and the Perak royal family, and partnering with local companies and celebrities on a postcard campaign that delivered the signatures of more than 80,000 individuals who supported protection to state and federal leaders.

These efforts achieved partial success in 2007, when the Perak state government established about one-third of Belum–Temengor as the Royal Belum State Park (28). The rest of the area remained open to logging, however, and by establishing the park under state law instead of the National Parks Act, the state government retained authority to reopen it for logging. Such excisions have occurred in other Malaysian states (29). Lack of national park status also reduces access to federal resources to combat poaching, which remains a serious problem (30).

The state government has been reluctant to protect Belum–Temengor more completely and more permanently against logging due to a concern over lost revenue and jobs (31). We conducted the household survey to determine if Malaysian households outside of Perak were satisfied with partial protection of Belum–Temengor or would prefer a higher level of protection, in the sense of being willing to pay an amount that would cover the opportunity costs to the state and the direct costs of protection against poaching. Because the policy issue was not simply whether to protect the forest, but how large an area to protect and against which threats—logging, poaching, or both—we designed the choice experiments to generate data for estimating households' WTP for different levels and types of protection (*SI Text*, section 2).

We depicted protection against poaching as providing a single benefit, reduced extinctions in Belum–Temengor, and protection against logging as providing two benefits, reduced extinctions in Belum–Temengor and reduced flooding in Perak (not in Selangor or Kuala Lumpur). We described poaching as affecting mainly large mammals; and logging as affecting mainly smaller mammals, reptiles, amphibians, and insects (*SI Text*, section 2).

We found that mean household WTP was significantly greater than zero for both types of protection (*SI Text*, section 2): expressed as monthly payments to protect 100,000 ha and with 99% confidence intervals in parentheses, US$1.08 (US$0.91–1.25) for logging and US$0.71 (US$0.62–0.80) for poaching. These amounts were equivalent to about 0.1% of mean monthly income for households in Selangor and Kuala Lumpur. Households were willing to pay a monthly premium of US$0.67 (US$0.57–0.76) for plans that supplied maximum protection (all 300,000 ha protected against both threats), over and above the sum of WTP for complete protection against the two threats calculated separately. Given the physical separation of Belum–Temengor from the surveyed locations and limited recreational access to Belum–Temengor as of 2010 (28), the households' WTP probably reflects mainly existence, option, and bequest values (32), although it might also reflect expectations about future recreational use.

We estimated societal WTP to protect all of Belum–Temengor against both logging and poaching by multiplying these mean estimates by the number of households in Kuala Lumpur and Selangor (Table 2). We compared this measure of societal benefits to the societal costs, which included opportunity costs and direct management costs (*SI Text*, section 3). We found that the societal benefits were nearly twice as large as the societal costs (Table 2). This likely understates the true benefit–cost ratio, because it ignores benefits to the more than 70% of Malaysian households that do not live in Kuala Lumpur or Selangor and because our cost assumptions were likely to be upwardly biased (*SI Text*, section 3).

Expressed per hectare, annual societal WTP to protect Belum–Temengor, US$437, is much larger than the annual operating budgets of the two largest existing protected areas in Peninsular Malaysia, US$12.80 at Endau–Rompin and only US$0.98 at Taman Negara (2005 estimates converted to 2010 price levels) (33). This comparison suggests that Malaysian protected areas are extremely underfunded, which is also indicated by comparisons of conservation spending in Malaysia to spending in other countries (25, 33). We caution, however, that Malaysian households' incremental WTP to protect other forests in addition to Belum–Temengor would likely be lower than their WTP to protect the latter (*SI Text*, section 4).

Table 2. Conservative estimates of aggregate annual benefits and costs to the populations of Kuala Lumpur and Selangor of fully protecting all of Belum–Temengor

Item	Value
Benefits, US$ million/y	
WTP to protect against logging	70.3
WTP to protect against poaching	46.3
WTP premium for maximum protection	14.5
Total	131.2
Costs, US$ million/y	
Direct	10.1
Opportunity: forgone timber revenue	51.2
Opportunity: WTP for job creation	6.4
Total	67.7
Benefits − costs	63.4
Benefit/cost ratio	1.9

Estimates are at 2010 price levels. Original estimates in Malaysian ringgit were converted to US dollars using the 2010 official exchange rate (which equaled 3.22 ringgit per dollar). Benefits were aggregated across households by multiplying mean estimates per household by the number of households (1,812,734) in Selangor and Kuala Lumpur in 2010 (48).

Our estimate of the societal benefits of protecting Belum–Temengor is probably understated from a long-run perspective because it ignores future income growth. Analysis of the household-level WTP estimates (*Materials and Methods*) revealed a significant and positive association with income for monthly household incomes above US$2,329 for both logging ($P = 0.035$) and poaching ($P = 0.029$) (Table S3), but no significant association for incomes below this level. At the mean household size in the sample, this monthly income threshold is equivalent to an annual per capita income of US$6,223. This is within the World Bank's UMI range and provides a microlevel complement to the macrolevel evidence in Table 1 that income at the UMI level is associated with a substantial increase in conservation demand.

On average, a 1% increase in income above this threshold was associated with 0.26% and 0.27% increases in WTP for protection against logging and poaching, respectively (Table S3). This less-than-proportional relationship mirrors results from metaanalyses of conservation valuation studies, which report estimates in the range of 0.38% (17) to 0.5–0.8% (18). A downward bias due to measurement error (our survey recorded household income as being within given ranges, not as exact values) might explain why our estimates are smaller than these. A positive effect of Malaysian economic development on WTP for conservation is also suggested by the trend in per capita donations to WWF Malaysia, which increased more than 10-fold in inflation-adjusted terms between 2002 and 2012 (*SI Text*, section 1).

Discussion

Our cross-country analyses and Malaysian case study provide evidence of a significant increase in public demand for conservation in relatively wealthier tropical countries, which has not been matched by protective actions by the countries' governments. This delayed government response likely has multiple explanations. One is imperfect information: Governments may simply not know what the public wants. Only one of the two recurrent cross-country public-opinion surveys in our cross-country analyses contained a question about biodiversity loss, and that question was added only recently and referred to global biodiversity loss, not loss in the countries surveyed (Table S2). Moreover, both surveys covered only a small minority of tropical countries. In Malaysia, survey-based information on public preferences for protecting Belum–Temengor did not exist before we conducted our survey. Providing policymakers with better information on public preferences is an important potential contribution of environmental valuation surveys in developing countries (34), but to our knowledge no prior forest valuation study in any tropical country had surveyed a representative sample of rural and urban households at either a national or state/provincial level (*SI Text*, section 1).

A second explanation is imperfect political processes, which compound the impact of imperfect information. Countries that are less democratic tend to protect less land (15). Among all countries in the world, the average UMI tropical country was only at the 57th percentile of a commonly used democracy indicator, the World Bank's voice and accountability index (*SI Text*, section 1). Mean ratings were even lower for less wealthy tropical countries, which suggests that the positive effect of economic development on government conservation actions revealed by the cross-country analyses could be due in part to improved political institutions and not just income growth per se. Malaysia's rating puts it at the 34th percentile, which is below the mean for even lower-middle income tropical countries. A relative lack of voice and accountability in this UMI country may help explain the slow and incomplete progress toward protecting Belum–Temengor.

The Malaysian case also suggests a third explanation: the classic political economy problem of concentrated costs (forgone logging revenue and jobs within Perak) coinciding with dispersed benefits (WTP for protection being spread across many households outside Perak) (35). This situation is not unique to tropical countries; for example, the United States' 1964 Wilderness Act launched decades of court battles between the timber industry and conservation groups over protection of national forests against logging before large areas were protected under the Act (36, 37). It probably has a greater impact on conservation outcomes in tropical countries, however, due to information on the benefits of conservation being less abundant and NGOs being more poorly funded in these countries.

Delayed conservation action by tropical country governments has policy implications for international funding of tropical forest protection. Controlling for other factors, developing countries receive less biodiversity aid as per capita national income rises (7). This could create a funding gap if, as a result of delayed action, domestic funding does not increase sufficiently rapidly to offset the decline in external funding. There is evidence that this has happened: Data from a recent study on underfunding of biodiversity conservation (25) show that spending in tropical countries fell short of expected levels by the greatest amounts in countries in the UMI group (*SI Text*, section 1). Malaysia is the seventh most underfunded country in the world according to that study (ref. 25, table 2).

The ranking of countries by degree of underfunding has been advocated as a guide for reallocating international conservation funding (25). Our findings suggest that increased domestic funding should also be emphasized in closing the funding gap, at least in UMI countries. A greater emphasis on domestic funding is also implied by a fourth possible explanation for delayed conservation action: Tropical country governments might be deliberately undersupplying domestic funding in a strategic attempt to attract increased external funding. This explanation comes from the general aid literature (38), and we know of no careful analysis of it for conservation aid.

The international community could facilitate increased domestic funding not only through the development of new funding mechanisms, such as payments for ecosystem services, but also by actions that address the factors that cause tropical country governments to lag behind their publics. Possible actions include funding the provision of better information on public preferences, supporting programs that aim to improve governance, strengthening local NGOs, and, to counter strategic underfunding by aid recipients (38), tying aid to specific projects implemented by donor country organizations and delegating aid responsibility to agencies whose primary mission is not conservation. Greater domestic funding resulting from these actions might have a positive feedback on international funding, as there is evidence that the public in donor countries favors recipient countries sharing the responsibility for tropical forest protection (39).

Our findings also have implications for international funding via REDD. Supplementary biodiversity payments have been proposed as a mechanism that would not only enhance biodiversity outcomes under REDD, but also achieve additional greenhouse gas emissions reductions (40). This proposal has been couched in terms of international funding for the biodiversity payments. Our findings provide an economic rationale for coupling international carbon payments made to UMI tropical countries under REDD with biodiversity payments funded by those countries themselves.

Materials and Methods

Analysis of Cross-Country CIs. To facilitate comparison across the CIs, we used identical regression specifications to model the indicators' association with income (*SI Text*, section 1). We tested mean differences between income groups by estimating

$$CI_{it} = c_i + \beta_{LI} LI_{it} + \beta_{LMI} LMI_{it} + \beta_{HI} HI_{it} + u_{it}.$$

LI_{it}, LMI_{it}, and HI_{it} are dummy variables indicating the income group (low, lower-middle, and high, respectively) for country i in year t. The number of countries and time periods depended on data availability for a given indicator (Tables S1 and S2). Because UMI is the omitted group, the regression coefficients (the βs) measure the mean difference in an indicator's level between these groups and the UMI group. c_i is a country fixed effect, which was included only for indicators with data for multiple time periods, and u_{it} is the error term. We used robust SEs (41, 42) clustered by country or country year, depending on data structure.

To test the significance of the association of an indicator with per capita GNI (PCGNI), which was measured in constant 2005 US dollars, we estimated

$$\ln(CI_{it}) = c_i + \beta_{PCGNI} \ln(PCGNI_{it}) + u_{it}.$$

Estimation procedures were otherwise identical to those for the income-group models. We interpreted the effect of PCGNI as a broad measure of various interrelated aspects of economic development, not a pure income effect; identifying the latter would require inclusion of additional controls. Although the correlation of PCGNI with other factors that tend to change with development therefore does not confound our interpretation of its effect, reverse causality could, but any resulting bias in the estimate of β_{PCGNI} is probably small (*SI Text*, section 1).

Household Survey. We followed a comprehensive survey development process aimed at addressing methodological problems that have often affected valuation studies in developing countries (43). Planning began in April 2007. During February 2008 to January 2010, we selected a Malaysian survey research firm through a competitive bidding process; designed the sampling plan in consultation with the Malaysian Department of Statistics; conducted 5 focus groups and 26 cognitive interviews, which generated drafts of the survey instrument; translated the instrument from English into Bahasa Malaysia, Mandarin, and Tamil, with reverse translation to check translation accuracy; and ran 3 pretests. We finalized the instrument and selected and trained enumerators during February to March 2010. We implemented the survey during April to June 2010. The survey was reviewed and approved by relevant committees within the Forest Research Institute Malaysia that function in a manner similar to an institutional review board, and informed consent was obtained from respondents.

We used a stratified two-stage sample design, with three strata: rural Selangor, urban Selangor, and Kuala Lumpur (entirely urban). We randomly selected 70 enumeration blocks (a Malaysian census unit) from each stratum in the first stage and 10 living quarters from each block in the second stage. The sample thus consisted of 2,100 living quarters. We successfully interviewed 1,261 households, for a 67% response rate after accounting for 210 living quarters that were either vacant or not occupied by Malaysian citizens.

Choice Experiments. Respondents were presented a series of four choice sets, each with three choice alternatives (forest management plans) (*SI Text*,

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section 2). One alternative in each set was the status quo. Each alternative had four attributes: area logged, area poached, jobs created, and cost. Each attribute had three levels: 0, 150,000, and 300,000 ha for the two area attributes (associated with none, half, and all of the corresponding threatened species going extinct); 2,500, 5,000, and 7,500 jobs created; and 2, 6, and 10 Malaysian ringgit per month for the cost attribute. The flood attribute was collinear with area logged (one, three, and five floods per year in Perak).

Analysis of Choice Experiment Responses. We fit a mixed logit model to the responses from the choice experiments (44, 45), with correlated random coefficients and SEs that were clustered by enumeration block (*SI Text*, section 2). The model included six explanatory variables: area protected against logging, area protected against poaching, jobs created, a dummy variable for the status quo alternative, a dummy variable for plans that supplied maximum protection (all 300,000 ha protected against both logging and poaching), and the cost of the plan (Tables S4 and S5). All coefficients were distributed normally except the coefficient on the cost of a plan, which was distributed log-normally (ref. 46, p. 611).

We used results from the mixed logit model to predict WTP for each respondent. We calculated individual-level parameters for the variables in the model using 250 Halton draws (47). Once these parameters were calculated, we calculated WTP by dividing a respondent's parameter for a given attribute of a plan by the respondent's parameter for the cost of the plan. The means and confidence intervals reported in the text were calculated with household size and ethnicity used as poststratification weights.

Analysis of Household WTP. We used multiple regression (ordinary least-squares with poststratification weights) to investigate the effects of socioeconomic variables on household WTP for protection against logging and poaching (*SI Text*, section 2). The variables were gross household income and household size; age, education, and ethnicity of the household head; and stratum. Coefficients on dummy variables for income categories indicated a threshold for the income effect between the fifth and sixth categories, so we reestimated the models using an income spline, with a knot at that point (Table S3).

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Supporting Information

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SI Text

1. Cross-Country Data: Sources and Notes

This section describes the data sources for the various cross-country variables cited in the main text. It also provides additional explanatory notes on data processing and analysis. We begin with the variables shown in Fig. 2. We then describe variables related to a series of statements made in the main text: decline in primary forest area, total forest area, years to reach upper-middle-income (UMI) status, other biodiversity indicators, representativeness of survey samples in forest valuation studies in developing countries, voice and accountability, and underfunding of biodiversity conservation. Finally, we describe the cross-country conservation indicators (CIs) shown in Table 1 and Tables S1 and S2.

Primary Forest Area and Threatened Endemic Species (Fig. 2). We identified countries as tropical using the classification system of the UN Food and Agriculture Organization's (FAO) Forestry Department (ref. 1, data table 2). We assigned these countries to the 2010 World Bank income groups using information in a spreadsheet prepared by the World Bank (OGHIST.xls; http://data.worldbank.org/about/country-classifications/a-short-history).

The spreadsheet contained 2010 income-group information for 107 of the FAO tropical countries, with information lacking for only a few small countries (mostly territories). The World Bank's income groups are based on gross national income (GNI) per capita and were defined as follows for 2010: low income, ≤US$1,005 (31 countries); lower-middle income, US$1,006–3,975 (36 countries); UMI, US$3,976–12,275 (27 countries); and high income, ≥US$12,276 (13 countries). Fig. 2 refers to these 107 tropical countries.

We obtained data on 2010 area of primary forest by country from the FAO Forestry Department. These data are also published in the FAO Forestry Department's *Global Forest Resources Assessment 2010* (ref. 2, table 8 in annex 3). The areas shown in Fig. 2 are low income, 13.1 million ha (1.6% of the total across the tropical countries in Fig. 2); lower-middle income, 167.4 million ha (21%); and UMI, 624.0 million ha (77%). High-income countries accounted for 0.8 million ha (0.1%) and are not shown in Fig. 2.

We obtained data on numbers of threatened endemic mammal, bird, and plant species from table 8 (2) entitled, "Total endemic and threatened endemic species in each country (totals by taxonomic group)," downloaded from The IUCN Red List of Threatened Species 2013.2 (www.iucnredlist.org/about/summary-statistics).

The totals shown in Fig. 2 are low income, 373 species (15% of the total across the tropical countries); lower-middle income, 848 species (34%); and UMI (49%), 1,213 species. High-income tropical countries, not shown in Fig. 2, had 62 species (2%).

The tropical countries included in Fig. 2 are listed by income group at the end of section 1. Some are located beyond the Tropics of Cancer and Capricorn (e.g., Bhutan, Nepal, Pakistan). We retained these countries in the sample to adhere to the FAO classification, given that several of our data series originated with the FAO Forestry Department. Had we excluded these countries, the UMI shares of primary forest area and threatened endemic species would have been even higher than indicated by Fig. 2. (The same would have been true if we had included China, which the FAO Forestry Department classifies as nontropical.) Spot checks indicated that excluding these countries barely changed the results of the analyses of CIs reported in Table 1.

Decline in Primary Forest Area. We state in the Introduction, "virtually all of the loss [of primary forests] is occurring in tropical countries." We base this statement on analysis of the FAO data on primary forest area, which indicated that 99.2% of global reduction in primary forest area during 2000–2010 occurred in tropical countries.

Total Forest Area. We state in *Results*, *Forests in UMI Countries*, "By 2010, nearly half of the global area of forests in tropical countries was in 27 countries classified by the World Bank as UMI." We obtained data on total forest area (kilometers squared) in 2010 by country from the World Bank's World Development Indicators (WDI) database (variable AG.LND.FRST.K2; http://databank.worldbank.org/data/views/variableSelection/selectvariables.aspx?source=world-development-indicators).

The original source of these data is the FAO Forestry Department's *Global Forest Resources Assessment 2010* (2). The totals were low income, 4,071,070 km^2 (22% of total forest area in tropical countries); lower-middle income, 5,965,270 km^2 (32%); UMI, 8,750,690 km^2 (46%); and high income, 43,630 km^2 (<0.25%).

Years to Reach UMI Status. We also state in *Results*, *Forests in UMI Countries*, "The UMI group is expanding: Only 9 of 27 countries were in it in 1990, and 9 additional tropical countries will join it within 25 y (and 10 more within 50 y) if 1995–2012 income growth rates continue." Determination of a country's income group in 1990 was based on the spreadsheet (OGHIST.xls) described above. Years to reach the UMI level were determined as follows: (*i*) We obtained data on per capita GNI (PCGNI) (constant 2005 US dollars) during 1995 to 2012 for tropical countries in the low- and lower-middle-income groups from the WDI (variable NY.GNP.PCAP.KD); (*ii*) we regressed the natural logarithm of PCGNI in each country on a time trend (year); (*iii*) we calculated the natural logarithm of the ratio of US$3,975 (the 2010 UMI lower threshold) to the country's 2010 PCGNI; and (*iv*) we divided the log ratio by the regression coefficient on time trend for the country. (The time periods thus refer to 25 and 50 y after 2010, not 2012.) The 9 countries predicted to reach UMI status within 25 y of 2010 were Angola, Belize, Bhutan, El Salvador, India, Indonesia, Nigeria, Sri Lanka, and Vietnam; the 10 countries predicted to reach it within 50 y were Bangladesh, Cambodia, Guatemala, Honduras, Lao People's Democratic Republic, Liberia, Mozambique, Nicaragua, the Philippines, and Rwanda.

This list of of 19 additional UMI tropical countries includes only 5 in Africa, which might underestimate the potential number of African entrants to that group during the next few decades. Radelet (3) identifies 17 African countries as emerging, in the sense that they are likely to sustain relatively rapid economic growth. These 17 countries include 15 tropical countries, of which only 4 were in the UMI group in 2010. That leaves 11 emerging African countries that could be on track to join the UMI group, double the number predicted by our analysis of 1995–2012 per capita GNI (PCGNI) growth rates. Radelet also identifies 6 additional African threshold countries, which are on the cusp of the emerging category. All are in the tropics.

Other Biodiversity Indicators. Another statement in *Results*, *Forests in UMI Countries* that requires documentation is that UMI countries "ranked highly according to several other biodiversity indicators" besides the number of threatened endemic species. We base this statement on four indicators: megadiversity (4), irreplaceable protected areas (5), the Global Environment Facility (GEF) benefits index (6), and the mammal global biodiversity fraction (GBF) (7). These indicators refer to years other than 2010, but to facilitate comparison with Fig. 2 we used the 2010 income groups when we analyzed them. We included only tropical countries in the analyses.

Mittermeier et al. (4) identified 17 countries as being megadiverse, meaning that they harbor an unusually large amount of biodiversity, as measured by both the total number of taxa and endemism. Thirteen of the 17 countries are tropical countries, with 2 being low income (Democratic Republic of the Congo and Madagascar), 4 being lower-middle income (India, Indonesia, Papua New Guinea, and the Philippines), and 7 being UMI (Brazil, Colombia, Malaysia, Mexico, Ecuador, Peru, and Venezuela). Four countries are not on the FAO tropical list (Australia, China, South Africa, and United States).

Le Saout et al. identified 137 global protected areas as being irreplaceable, in the sense of "ensuring representation of . . . all amphibians, nonmarine mammals, and birds," based on "the fraction of the global distribution of each species that is contained within each PA" (ref. 5, p. 803). Based on information in Table S2, most of the areas (118 of 137) are in tropical countries; of those, 71 (60%) are in UMI countries; 13 (11%) are in low-income tropical countries; 32 (27%) are in lower-middle-income tropical countries; and 2 (1.7%) are in high-income tropical countries. Nineteen of the areas are in seven countries classified as nontropical by the FAO (Australia, China, New Zealand, South Africa, United Kingdom, United States, and Yemen).

The GEF benefits index is a composite index that incorporates information on the types of habitat in a country, the number of species in the country, and the threat status for those species (6). It ranges from 0 (no biodiversity potential) to 100 (maximum biodiversity potential). We obtained 2008 data on the index for 107 tropical countries from the WDI (variable ER.BDV.TOTL.XQ). A linear regression of these data on dummy variables for the 2010 income groups, with the dummy excluded for the UMI group, yielded the following coefficients: low income, −10.6 ($P = 0.043$); lower-middle income, −4.98 ($P = 0.397$); and high income, −13.1 ($P = 0.012$). The negative signs indicate that the index is lower, on average, in countries in these groups than in countries in the UMI group, with the mean differences significant at the indicated P values, which are based on robust (Huber–White) SEs (8, 9). Overall regression statistics were $R^2 = 0.088$ and $F(3, 103) = 5.54$ ($P = 0.002$).

The mammal GBF was developed by Waldron et al. (7). It is constructed by determining the fraction of a mammal species' global range that occurs in a particular country, and then summing the fractions across all mammal species in the country. We obtained data on mammal GBFs for 99 tropical countries from the supporting information from ref. 7. As with the GEF benefits index, we regressed the country-level data for this indicator on dummy variables for the 2010 income groups, with the UMI dummy excluded and robust SEs used. This yielded the following coefficients: low income, −23.3 ($P = 0.210$); lower-middle income, −13.4 ($P = 0.503$); and high income, −46.3 ($P = 0.008$). The negative signs indicate that the mammal GBF is lower, on average, in countries in these groups than in countries in the UMI group, but as indicated the difference was significant at $P < 0.05$ only for the high-income group. Overall regression statistics were $R^2 = 0.037$ and $F(3, 95) = 9.32$ ($P < 0.0001$).

We considered including a fifth indicator, biodiversity hotspots, which are areas with both high rates of endemism and high rates of habitat loss. Myers et al. (10) identified 25 hotspots, and Conservation International expanded the number to 34 (www.conservation.org/where/priority_areas/hotspots/Pages/hotspots_main.aspx).

Most of the hotspots occur in multiple countries, and nearly all tropical countries have some area in at least one hotspot. For this reason, the number of countries with area in one or more hotspots does not provide a very discriminating indicator for comparing the four income groups.

Representativeness of Survey Samples in Tropical Forest Valuation Studies. We state in *Discussion*, "to our knowledge no prior forest valuation study in any tropical country has surveyed a representative sample of rural and urban households at either at national or state/provincial level." We based this statement on an extensive literature search and correspondence with a large number of environmental economists who specialize in valuation research in developing countries. We identified only one published valuation study that surveyed a nationally representative sample in a tropical developing country (Tanzania), but it focused on urban public services (in the case of the environment, water and sanitation) (11). We identified one province-level study on nature protection that surveyed both rural and urban households in a nontropical developing country (South Africa), but it excluded poor households (12).

Voice and Accountability. We also state in *Discussion*, "Among all countries in the world, the average UMI tropical country was only at the 57th percentile of a commonly used democracy indicator, the World Bank's voice and accountability index. Mean ratings were even lower for less wealthy tropical countries . . .." The voice and accountability index can be downloaded from the Worldwide Governance Indicators database (http://info.worldbank.org/governance/wgi/index.aspx?fileName=wgidataset.xlsx#home).

According to information on that site, "Voice and accountability captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media." The mean percentile ranks for tropical countries were low income, 26th percentile (i.e., the average country in this group had a voice and accountability rating that was higher than the ratings in 26% of the countries of the world); lower-middle income, 39th percentile; UMI, 57th percentile; and high income, 60th percentile.

Underfunding of Biodiversity Conservation. A final statement in *Discussion* that requires documentation is, "data from a recent study on underfunding of biodiversity conservation show that spending in tropical countries fell short of expected levels by the greatest amounts in countries in the UMI group." We base this claim on data in table S1 from Waldron et al. (7), which shows country-level estimates of "spending inadequacy": average expenditure on biodiversity conservation during 2001–8, minus the amount of expenditure that was expected given a country's characteristics. Expenditure includes funds from all sources, external as well as domestic. The table includes estimates for 124 countries, of which 73 are tropical. (Tanzania appears twice; we ignored the second instance, ranked 123 in the table.) Summing the estimates across the countries in a given income group yielded the following totals, with the number of countries in each group in parentheses:

Low: US$135.44 million (38)
Lower middle: −US$22.68 million (21)
Upper middle: −US$116.59 million (12)
High: −US$1.53 million (2)

The positive sign for low-income countries indicates that the authors estimated higher-than-expected spending for the countries in that group. (Their estimates show that funding in those countries was mainly from external sources: Summed across countries, foreign aid accounted for 63% of total funding in low-income countries, compared with 55% in lower-middle-income countries, 36% in UMI countries, and 20% in high-income countries.) Spending was below the expected amount by the greatest amount in the UMI group, not only in the aggregate but also per country: about US$10 million per country, compared with about US$1 million per country for the other two groups.

CIs. This section describes data sources and provides additional information on the analyses of the six cross-country CIs in Table 1. Data on these indicators were available for multiple years for each country (i.e., panel data), which enabled us to use fixed-effects models to control for unobserved country characteristics that could confound the indicators' association with income. Table S1, which is a more detailed version of Table 1, provides information on the numbers of countries and years included in the samples for each indicator. Econometric methods applied to the data are described in *Materials and Methods*, with deviations from those methods documented in the notes to Table S1. Table S1 also provides coefficient estimates for the high-income group for the last two indicators in Table 1; samples for the other four indicators did not contain any countries in that group. Samples for all of the indicators included only countries classified as tropical by FAO.

The country fixed effects in our panel models do not control for time-varying country characteristics. Given that we are using PCGNI (and the World Bank's income groups, which are based on it) as a broad measure of economic development, we are not concerned with the tendency of PCGNI to be correlated with other country characteristics that change with development, such as improved governance. In fact, these correlations are what allow us to interpret PCGNI as a broad development measure. We would need to be concerned about these correlations only if we were attempting to identify the effect of income as distinct from the effects of these correlated characteristics. Our interpretation of the association between the CIs and PCGNI (and the income-group dummies) could be confounded, however, by reverse causality: For example, an increase in a CI causing a contemporaneous increase in PCGNI as a result of increased supply of ecosystem services. If so, then our estimates of β_{PCGNI} would be biased upward. Available evidence indicates that the effect of forest ecosystem services on national income is small, however (13), and so this bias is unlikely to be great.

Due to the inclusion of the country fixed effects, differences in mean values of the CIs between income groups (i.e., central columns of Table 1) were identified by changes in the income-group status of individual countries over time. If the samples for the indicators included countries whose income group did not change during the sample period, then the numbers of observations shown in Table 1 overstate the effective sample sizes used to identify the mean differences. For each indicator, the share of the total observations in the estimation sample that came from countries whose income group changed during the sample period was as follows: World Values Survey, 13.7%; AmericasBarometer, 36.8%; domestic donations to the World Wildlife Fund (WWF), 54.8%; cofinancing of GEF projects, 48.8%; land area in terrestrial protected areas, 51.9%; and land area in forests protected for biodiversity conservation, 43.5%. Shares of country years in the samples were very similar: World Values Survey, 15.9% (7 country years); AmericasBarometer, 35.1% (27 country years); domestic donations to WWF, 54.8% (23 country years); cofinancing of GEF projects, 45.2% (138 country years); land area in terrestrial protected areas, 51.9% (1187 country years); and land area in forests protected for biodiversity conservation, 43.5% (157 country years).

For the first three indicators, these values indicate that identification of mean differences was based on a narrow information base in either relative or absolute terms (or both, for the first indicator). The underlying cause was the small number of countries and short sample periods for these indicators. This reinforces a point in *Discussion*, that there is a relative lack of information on public concern about conservation in tropical developing countries. It also corroborates a point by Waldron et al. (7), that financial data on conservation nongovernmental organization (NGOs) are scarce.

We also compiled and analyzed data on six other CIs that were based on purely cross-sectional data (i.e., a single time period per country). We present results from regression analyses of these additional indicators in Table S2. The analyses paralleled those for the panel data indicators. Samples were restricted to tropical countries, and results from two regression models are shown for each indicator: (*i*) coefficient estimates from a regression that related the indicator to income-group dummies (excluded dummy: UMI); and (*ii*) the estimated elasticity from a regression that related the indicator to PCGNI (constant 2005 US dollars).

Table 1 and Tables S1 and S2 show exact *P* values for coefficient estimates and elasticities. We do not duplicate this detail below when discussing results but instead refer to broad significance levels (e.g., 0.01, 0.05, 0.1, 0.15, 0.2). We do, however, cite exact *P* values for *F* tests of overall model significance, as they are not included in the tables.

Indicators Based on Panel Data (Table 1 and Table S1). ***Public opinion: World Values Survey.*** We downloaded World Values Survey data from www.wvsevsdb.com/wvs/WVSData.jsp. The following question was included in the three most recent survey waves:

> Here are two statements people sometimes make when discussing the environment and economic growth. Which of them comes closer to your own point of view? A. Protecting the environment should be given priority, even if it causes slower economic growth and some loss of jobs. B. Economic growth and creating jobs should be the top priority, even if the environment suffers to some extent.

We coded the responses as "1" if respondents selected "A" and "0" if they selected "B." Given the binary nature of this variable, we used logistic regression instead of least-squares to estimate the elasticity model. A new sample of households was drawn for each wave, and so the data were a panel at the level of countries but not households.

Results indicate that the fraction of households selecting response A in UMI countries was 0.276 higher than in low-income countries and 0.116 higher than in lower-middle-income countries, with both differences significant at $P < 0.01$. Overall regression statistics for the model with income-group dummies were $R^2 = 0.085$ and $F(30, 54{,}027) = 167$ ($P = 0.0001$); and for the model with PCGNI, pseudo-$R^2 = 0.067$ and χ^2 $(28) = 4{,}655$ ($P = 0.0001$).

Public opinion: AmericasBarometer. We downloaded AmericasBarometer data from www.vanderbilt.edu/lapop/survey-data.php. Five survey waves included the following open-ended question, "In your opinion, what is the most serious problem faced by the country?" AmericasBarometer surveys have also been conducted in Africa and Asia but have not included this question. We coded responses as 1 if they were labeled "environment" in the dataset and 0 otherwise. As in the analysis of the World Values Survey data, we used logistic regression instead of least-squares to estimate the elasticity model, and so the data were a panel at the level of countries but not households.

Results indicate that the fraction of households selecting "environment" in UMI countries was 0.00797 higher than in low-income countries and 0.00511 higher than in lower-middle-income countries, with these differences significant at $P < 0.05$ and $P < 0.15$, respectively: For overall regression statistics, the model with income-group dummies were $R^2 = 0.011$ and $F(2, 76) = 5.85$ ($P = 0.005$); and the model with PCGNI was pseudo-$R^2 = 0.097$ and χ^2 $(17) = 142$ ($P = 0.0001$).

Domestic donations to WWF. Financial data on conservation NGOs are difficult to obtain. In their supporting information, Waldron et al. (7) observed, "We requested financial data several times from all these international NGO organizations but none were able or willing to provide country-level spending breakdowns." We focused on WWF, which we believe is the NGO with the largest number of country chapters in tropical countries and relies the most heavily on domestic donations to fund its programs. WWF is a decentralized organization that does not have a common database with financial information on its country chapters. We extracted donation data from annual reports downloaded from websites for the country chapters. Not all country chapters prepare publicly available annual reports, and those that prepare them define revenue sources in ways that vary across country.

Among all tropical countries, we identified only the five listed below as having WWF chapters that produced annual reports that met two criteria: the reports contained data on revenue sources for three or more years, and the revenue data distinguished domestic donations from other sources (e.g., international, corporate, government).

Brazil: www.wwf.org.br/informacoes/bliblioteca/relatorioanual/ (2004–2012)
India: www.wwfindia.org/wwf_publications/annual_report/ (2006–2011)
Malaysia: www.wwf.org.my/media_and_information/publications_main/ (2002–2012)
Pakistan: www.wwfpak.org/publication/annualreport.php (2005–2012)
Philippines: http://wwf.org.ph/wwf3/wwa/annualrep (2004–2012)

A sixth country chapter, for Indonesia, met the first criterion but not the second. We converted the donations to constant 2005 US dollars per thousand people. In some instances, we also needed to convert from fiscal years to calendar years. For example, if the fiscal year was July 1, 2006–June 30, 2007, we allocated half of the donations to 2006 and half to 2007. We included in the analysis only years for which we were able to construct estimates for a complete calendar year. Those years are shown above in parentheses.

Results indicate that domestic donations per thousand people in UMI countries were approximately US\$1.03 higher than in low-income countries and US\$0.77 higher than in lower-middle-income countries, with only the former difference being significant at even $P < 0.1$. Overall regression statistics for the model with income-group dummies were $R^2 = 0.691$ and $F(6, 35) = 68.8$ ($P = 0.0000$); and for the model with PCGNI, $R^2 = 0.982$ and $F(5, 36) = 225$ ($P = 0.0001$).

In the particular case of Malaysia, donations expressed per thousand people and in constant 2005 US dollars rose from US \$9.09 in 2002 to US\$139.07 in 2012.

Percent cofinancing of GEF forest biodiversity projects. We downloaded data on all approved biodiversity projects funded by the GEF because the inception of the organization from the GEF Data Mapping Portal (www.thegef.org/gef/RBM). Data from this source do not specify the ecosystems (e.g., tropical forests) that were protected by the projects; this information must be inferred from the project titles. We thus applied a series of filters to identify projects that likely pertained to forests in tropical countries. We began by dropping projects that were not in tropical countries or were regional projects that could not be assigned to specific countries. We then dropped projects that supported enabling activities, which could pertain to many ecosystems besides forests; projects with "grassland" or "desert" in their titles; projects with "marine" or "fish" in their titles; and projects that had "lake" or "river" in their titles but not "basin" or "watershed"; and projects with "agri," "agro," "crop," "farm," "ranch," or "livestock" in their titles. Finally, we dropped projects without information on funding. The final list included 369 projects.

We defined the year of a project as the year it was approved by the GEF Secretariat (the variable "fy approval" in the GEF database). We defined the cofinancing share as the ratio of the reported amount of cofinancing (the variable "cofinancing") to the sum of that variable and the funding provided by the GEF ("GEF fund"). Host countries are responsible for raising the indicated amount of cofinancing, which helps ensure that GEF funding only covers the incremental cost of project activities beyond those that generate benefits for the country itself. We expressed the cofinancing share as a percentage.

Results indicate that the cofinancing share in UMI countries was 24.7 percentage points higher than in low-income countries and 12.0 percentage points higher than in lower-middle-income countries, with both differences significant at $P < 0.01$. Overall regression statistics for the model with income-group dummies were $R^2 = 0.263$ and $F(2, 81) = 5.65$ ($P = 0.005$); and for the model with PCGNI, $R^2 = 0.220$ and $F(1, 61) = 10.7$ ($P = 0.002$).

Percent land area in terrestrial protected areas. We obtained data on terrestrial protected area (percentage of total land area) from the WDI (variable ER.LND.PTLD.ZS). Results indicate that the share of land area in protected areas in UMI countries was 3.18 percentage points higher than in low-income countries and 1.94 percentage points higher than in lower-middle-income countries, with both differences significant at $P < 0.01$. The share in UMI countries was 2.48 percentage points lower than in high-income countries, with the difference significant at $P < 0.15$. Overall regression statistics for the model with income-group dummies were $R^2 = 0.903$ and $F(3, 104) = 8.05$ ($P = 0.0001$); and for the model with PCGNI, $R^2 = 0.943$ and $F(1, 94) = 10.8$ ($P = 0.001$).

Percent land area in forests protected for biodiversity conservation. We obtained country-level data on area of forest protected for biodiversity conservation from the FAO Forestry Department (data available upon request). We converted it to a percentage by dividing by a country's total land area (WDI variable AG.LND.TOTL.K2). Results indicate that the share of land area in forests protected for biodiversity conservation in UMI countries was 0.758 percentage points higher than in low-income countries and 0.418 percentage points higher than in lower-middle-income countries, with the former difference significant at $P < 0.1$ and the latter only at $P < 0.3$. The share in UMI countries was 0.110 percentage points lower than high-income countries, with the difference significant only at $P < 0.6$. Overall regression statistics for the model with income-group dummies were $R^2 = 0.964$ and $F(3, 94) = 1.50$ ($P = 0.220$); and for the model with PCGNI, $R^2 = 0.984$ and $F(1, 88) = 3.31$ ($P = 0.072$).

Indicators Based on Cross-Sectional Data (Table S2). As discussed in *Results*, *Malaysian Case Study: Protecting Belum–Temengor Against Logging and Poaching*, the analyses of the purely cross-sectional indicators are subject to the risk that the estimated association of the indicators with income is confounded by unobserved country characteristics. With this caution in mind, we note that the results in Table S2 exhibit the same patterns as the results in Table 1 and Table S1: On average, the indicators in UMI countries are greater than in low- and lower-middle-income countries, with most of the differences being significant at $P < 0.05$ (and all at $P < 0.1$); and income elasticities are positive and significant ($P < 0.001$ in most cases). Differences between UMI and high-income countries are not significant for most of the indicators at even $P < 0.2$.

Public opinion: World Values Survey. The data source for this indicator, the World Values Survey, was the same as for the first indicator in Table 1. The following question was included in the 2005–8 survey wave: "Now let's consider environmental problems in the world as a whole. Please, tell me how serious you consider each of the following to be for the world as a whole. Is it very serious, somewhat serious, not very serious, or not serious at all?" The enumerator stated three problems, one of which was "Loss of plant or animal species or biodiversity"; the other two were "Global warming or the greenhouse effect" and "Pollution of rivers, lakes, and oceans." We coded responses to the question about loss of species/biodiversity as 1 if respondents selected "very serious" and 0 otherwise. Given the binary nature of this variable, we used logistic regression instead of least-squares to estimate the elasticity model.

Results indicate that the fraction of households selecting "very serious" in UMI countries was 0.0720 higher than in low-income countries and 0.278 higher than in lower-middle-income countries, with both differences significant at $P < 0.01$. The fraction in UMI countries was 0.142 lower, however, than in high-income countries ($P < 0.01$). Overall regression statistics for the model with income-group dummies were $R^2 = 0.041$ and $F(3, 21{,}308) = 334$ ($P = 0.0001$); and for the model with PCGNI, pseudo-$R^2 = 0.098$ and χ^2 (13) = 2,276 ($P = 0.0001$).

Number of environmental NGOs. We obtained data on number of environmental NGOs per country from M.T. Buntaine (University of California, Santa Barbara, CA). Various print editions of the *Environment Encyclopedia and Directory* were the original source of these data, with data for years 1994, 1997, and 2001 having been recorded from this source by E. Neumayer (Department of Geography and Environment, London School of Economics, London) and data for 2005 and 2010 recorded by Buntaine. A paper by Buntaine provides additional information on the data (14).

We analyzed only the 2005 data for three reasons. First, data were available for many more tropical countries in that year than in the earlier years. Second, data for earlier years were not comparable to the data for 2005, as NGOs with multiple branches or offices were coded as a single organization starting in 2005 but as multiple organizations in prior years. Third, data for 2010 were not comparable to the data for 2005, as the organizations that had updated their entries for 2010 (instead of just repeating the 2005 entries) was not indicated.

We used data on total national population (WDI variable SP.POP.TOTL) to express the number of environmental NGOs per million people. Results indicate that, on average, UMI countries had 15.1 more environmental NGOs per million people than low-income countries and 13.2 more than lower-middle-income countries, with these differences significant at $P < 0.05$ and $P < 0.1$, respectively. Overall regression statistics for the model with income-group dummies were $R^2 = 0.143$ and $F(3, 102) = 4.67$ ($P = 0.005$); and for the model with PCGNI, $R^2 = 0.082$ and $F(1, 96) = 3.95$ ($P = 0.050$).

Domestic budget for protected areas per kilometers squared. We recorded data for this indicator from two reports, James et al. (ref. 15, table 1) and Mansourian and Dudley (16, table 3). The former was the first study to estimate national budgets for protected areas for a large number of countries. It also provided information on foreign funding, which we excluded from the data we analyzed. Mansourian and Dudley updated the domestic budget estimates for a subset of the countries covered by James et al. The number of countries that appeared in both datasets was too small to allow estimation by a fixed-effects model. Given that the data for this indicator came from two different sources, we included in the regressions a dummy variable to control for potential differences in data gathering and data processing between the sources. The estimates were expressed in US dollars per kilometer squared but referred to a wide range of years (1990–2007); we used the US gross domestic product (GDP) deflator (from the WDI) to convert the estimates to a common base year (2005).

Results indicate that, on average, UMI countries spent US $9,760/km^2 more than low-income countries and US$9,470/km^2 more than lower-middle-income countries, with both differences significant at $P < 0.1$. Overall regression statistics for the model with income-group dummies were $R^2 = 0.258$ and $F(4, 74) = 2.07$ ($P = 0.094$); and for the model with PCGNI, $R^2 = 0.211$ and $F(2, 53) = 2.48$ ($P = 0.093$).

Domestic conservation spending per capita. We obtained data for this indicator from the supporting information for Waldron et al. (7), which, according to the authors (p 12,144), is "the most complete database of global conservation spending yet published." Their supporting information includes a spreadsheet (sd01.xls). We analyzed the variable labeled "total domestic funding." This variable estimates mean annual conservation spending from domestic sources during 2001–2008, expressed in 2005 US dollars. It includes spending on programs other than just protected areas and thus represents a more comprehensive expenditure indicator than the preceding indicator based on data in the papers by James et al. and Mansourian and Dudley. We converted it to a per capita measure by dividing by mean annual total population during 2001 to 2008, using the WDI variable mentioned above. As with the other indicators that we analyzed, we limited the sample to tropical countries. We restricted the sample further by mimicking Waldron et al. and excluding the data-insufficient countries listed in their table S3.

Results indicate that, on average, UMI countries spent US $2.47 per capita more than low-income countries and $2.07 per capita more than lower-middle-income countries, with these differences being significant at $P < 0.05$ and $P < 0.1$, respectively. Overall regression statistics for the model with income-group dummies were $R^2 = 0.379$ and $F(3, 83) = 4.30$ ($P = 0.007$); and for the model with PCGNI, $R^2 = 0.158$ and $F(1, 83) = 5.59$ ($P = 0.020$).

Domestic conservation spending as a percentage of the total. This indicator is the same as the previous one except that it expresses the total domestic spending variable from Waldron et al. (7) as a percentage of their total spending variable (which is the unlabeled variable in column B of their spreadsheet, sd01.xls). According to this indicator, domestic spending relative to total spending in UMI countries was 29.7 percentage points higher than in low-income countries and 31.7 percentage points higher than in lower-middle-income countries, with both differences significant at $P < 0.01$. Domestic spending relative to total spending in UMI countries was 27.7 percentage points lower, however, than in high-income countries ($P < 0.01$). Overall regression statistics for the model with income-group dummies were $R^2 = 0.169$ and $F(3, 81) = 5.50$ ($P = 0.002$); and for the model with PCGNI, $R^2 = 0.137$ and $F(1, 82) = 13.4$ ($P = 0.001$).

Domestic public expenditures on forestry as a percentage of the total. We obtained 2005 country-level data on operating expenditures on forestry from the FAO Forestry Department. These data are also published in the FAO Forestry Department's *Global Forest Resources Assessment 2010* (ref. 2, table 19 of annex 3). They refer to all forest-related programs implemented by public agencies, not only conservation programs, and they were disaggregated by source, domestic vs. external. We expressed domestic expenditure as a percentage of the total (= domestic + external).

Domestic expenditure relative to total expenditure in UMI countries was 37.8 percentage points higher than in low-income countries and 23.0 percentage points higher than in lower-middle-income countries, with both differences significant at $P < 0.01$. Overall regression statistics for the model with income-group dummies were $R^2 = 0.20$ and $F(3, 40) = 9.16$ ($P = 0.0001$); and for the model with PCGNI, $R^2 = 0.108$ and $F(1, 44) = 5.17$ ($P = 0.028$).

2. Choice Experiments: Design and Econometric Analysis

This section provides detail on the design of the choice experiments, including justification for the assumed linear relationship

Tropical countries included in Fig. 2 by 2010 income group

Low (31)	Lower middle (36)	Upper middle (27)	High (13)
Bangladesh	Angola	American Samoa	The Bahamas
Benin	Belize	Antigua and Barbuda	Barbados
Burkina Faso	Bhutan	Botswana	Bermuda
Burundi	Bolivia	Brazil	Brunei Darussalam
Cambodia	Cameroon	Colombia	Cayman Islands
Central African Republic	Cape Verde	Costa Rica	Equatorial Guinea
Chad	Republic of Congo	Cuba	French Polynesia
Comoros	Cote d'Ivoire	Dominica	Guam
Democratic Republic of Congo	Djibouti	Dominican Republic	New Caledonia
Eritrea	El Salvador	Ecuador	Puerto Rico
Ethiopia	Fiji	Gabon	Singapore
The Gambia	Ghana	Grenada	Trinidad and Tobago
Guinea	Guatemala	Jamaica	Virgin Islands (United States)
Guinea-Bissau	Guyana	Malaysia	
Haiti	Honduras	Maldives	
Kenya	India	Mauritius	
Liberia	Indonesia	Mexico	
Madagascar	Kiribati	Namibia	
Malawi	Lao People's Democratic Republic	Panama	
Mali	Mauritania	Peru	
Mozambique	Nicaragua	Seychelles	
Myanmar	Nigeria	St. Kitts and Nevis	
Nepal	Pakistan	St. Lucia	
Niger	Papua New Guinea	St. Vincent and the Grenadines	
Rwanda	Paraguay	Suriname	
Sierra Leone	Philippines	Thailand	
Somalia	Samoa	República Bolivariana de Venezuela	
Tanzania	Sao Tome and Principe		
Togo	Senegal		
Uganda	Solomon Islands		
Zimbabwe	Sri Lanka		
	Sudan		
	Tonga		
	Vanuatu		
	Vietnam		
	Zambia		

The numbers in parentheses represent the number of countries for each income group.

between species extinctions and areas affected by logging or poaching, and the econometric analysis of the responses to the experiments. We are grateful to Jordan Louviere (Institute for Choice, University of South Australia, Adelaide, Australia) for assistance with the design of the choice experiments.

Choice Experiment Design. The experimental design for the choice experiments struck a balance between the amount of information gleaned from each respondent and the survey burden on the respondents. These two issues were closely related to the length of the survey and the ability to estimate respondent preferences for changes in the attributes of interest given technical and perceptual constraints on the relationships between attribute levels. As will be highlighted below, the more common and parsimonious orthogonal main effects (OME) design was inappropriate given our desire to allow for and investigate possible synergistic effects across forest management plans (in particular, maximum protection against both logging and poaching). The inclusion of a status quo alternative with nonzero attribute levels also played a part in our decision not to use an OME design, as did the imposition of a particular relationship, deemed important by respondents, between the level of logging and the cost of the plans.

The configuration of our choice sets—four choice sets, each with three choice alternatives (forest management plans), where one of the alternatives was the current status quo—is one of the more typical discrete choice experiment (DCE) configurations (17, 18). Before the presentation of the choice sets, substantial information was presented to the respondents about Belum–Temengor verbally and on show cards. Each choice set was presented on a separate show card with attributes displayed in tabular form. This presentation was designed to encourage consideration of the attributes of competing plans, including cost, against the status quo alternative, which involved no improvements but also, importantly, no increase in cost. (Despite the 2007 creation of Royal Belum State Park, which covers about one-third of Belum–Temengor, we presented the status quo as allowing all of Belum–Temengor to be logged, because the establishment of the park under state law instead the federal National Parks Act allows the Perak state government to reopen it for logging. None of the survey respondents or participants in the focus groups or cognitive interviews objected to this definition of the status quo. Moreover, our survey results indicate that 66% of households in Selangor and Kuala Lumpur have not heard of Belum–Temengor.) The show card for one of the choice sets is included at the end of section 2.

The forest management plans posed three special challenges from the perspective of designing the DCE. The first, discussed in more detail below, was that we had a status quo alternative with fixed nonzero attribute levels (e.g., the status quo plan involved poaching and logging) other than cost, which was zero. The second challenge involved defining the relationship between two attributes of interest: (*i*) how many floods would occur in Perak in an average year (not in Selangor or Kuala Lumpur, which are not in the same river basin as Belum–Temengor), and (*ii*) the amount of logging that would occur in Belum–Temengor. We assumed that the number of floods was positively and significantly correlated with the area logged. Given the goal to value the benefits of protecting forests against logging, there was no need to estimate separate effects for floods and logging; hence, the experimental design included a single attribute, logging, which was uniquely tied to a specific logging level (i.e., area affected by logging) and represented the impacts on both floods and extinctions of species affected by logging. (See *Effects of Forest Protection on Species Extinctions* for a more detailed discussion of the assumed relationship between extinctions and areas affected by logging or poaching.) The estimated parameter on this attribute in our choice models reflected the joint benefit of reduced flooding and reduced species extinctions, with neither benefit being separately identifiable. Nevertheless, we incorporated the technical relationship between logging and flooding into the list of attributes and attribute levels shown to the respondents by separately displaying rows (attributes) giving floods and logging levels, just as we included a row displaying extinctions.

The third challenge was a perceptual issue that arose during the development work for the survey. Some participants in our focus groups and cognitive interviews voiced skepticism that plans that had less logging (i.e., more protection against logging) could have a lower cost than programs with more logging. This perspective, although not a hard technical constraint, is likely to hold in practice. Failing to address this skepticism would have undermined realism, which is highly desirable when presenting respondents with choices among the plans. We incorporated this constraint with a nested design such that, within the set of alternatives that was presented to a respondent in a given choice set, lower levels of logging were always associated with higher costs. These levels were randomly shifted across respondents and choice sets to ensure that both cost and logging parameters were statistically identifiable.

In an ideal world, a full factorial design could be used that would allow all possible model parameters related to the attributes and their levels to be estimated. However, because of the combinatoric nature of attributes and levels, under such a design each respondent would need to be asked several thousand questions so that the parameter estimates for each attribute and combination of attributes could be statistically identified. A more common approach, and one that is less daunting to survey respondents, is to use an OME design. This design is straightforward to implement but has the drawback that the interaction terms are not generally identified. Our nonzero status quo level made the OME design a bit more problematic and, perhaps more importantly, would have restricted our ability to estimate some of the key two-way interaction terms we needed to include and evaluate.

Consequently, we used a more sophisticated balanced incomplete block design with foldovers to help identify key interactions. A balanced incomplete design is characterized by three conditions: (*i*) Each treatment (a pair of policy alternatives) occurs at most once in any given block (the group of choice sets seen by a respondent), which prevents a respondent from seeing the same policy choice twice; (*ii*) each treatment occurs in a specified number of blocks; and (*iii*) each pair of treatments occurs together in the same block a specified number of times across the set of blocks. The latter two conditions ensure desirable properties for estimating the model related to parameter identification.

With each respondent receiving a block of 4 choice sets and each choice set containing 3 alternatives, each respondent saw a total of 12 policies where 4 of those policies were the status quo policies. Each policy alternative had four attributes (area logged, area poached, jobs created, and cost; the flood attribute was collinear with area logged), and each attribute had three levels. Given the nesting of logging and cost, the natural combinatoric was 27; so, our balanced incomplete design had 27 blocks of 4 policy pairs. A foldover design rotates each attribute level by one level. With 3 attributes, it is possible to do this in both directions from the original 27 program pairs, thereby creating 81 blocks of 4 policy pairs. Consequently, this foldover design unaliases the first-order interactions by eliminating their confounding effects with higher-order interactions, thereby allowing their statistical identification. We took the 81 blocks of 4 policy pairs, added the status quo, and shuffled the order of sets by randomly renumbering them.

The 1st household number (living quarter) to be included in the sample was assigned to the first (randomly renumbered) block of four policy alternatives, the second to the 2nd block of policy alternatives, and so on until the 82nd household number was reached. At this point, the process was repeated until the end of the sample was reached, thereby creating multiple replicants of the same blocks of choice sets on the order of the sample size divided by 81. Because of random variation in which households did not respond to the survey, there were minor variations in the number of replicants (~15) of each of the 81 blocks of 4 policy alternatives in the sample of completed surveys. Keep in mind that the status quo was fixed.

Effects of Forest Protection on Species Extinctions. Increased forest protection was described to respondents as reducing the local extinction of two different groups of species. Poaching was described as affecting mainly large charismatic megafauna. A substantial literature details the impacts of poaching on tropical biodiversity (19, 20). Logging was described as affecting a broader range of generally smaller organisms. A growing (21) but uncertain (22) literature explicates the overall negative impact of timber harvests in primary forests on tropical biodiversity. A meta-analysis of the impacts of human disturbance on tropical forests underscores this point by concluding that, "primary [i.e., unlogged] forests are irreplaceable for sustaining tropical biodiversity" (21, p 378).

The effects of logging and poaching on extinction were described to respondents as being proportional to the area affected by each threat, with three levels being presented: None of the species affected by the threat would go extinct if none of the area was affected by it, half of the threatened species would go extinct if half the of area was affected, and all of the threatened species would go extinct if all of the area was affected. With the area attributes being perfectly colinear with extinctions, separate attributes were not needed for extinctions in the choice experiments. As in the case of the colinearity of number of floods with area logged, the show cards for the choice sets displayed information on extinctions in addition to information on areas affected by logging and poaching.

It is known that species loss scales with habitat area lost, but the rate is debated (23). Although the classical species–area relationship predicts a nonlinear relationship between number of species extinctions and area lost, the relationship has recently been updated to incorporate matrix and edge effects (24). Depending on species' sensitivities to disturbance, logging—which fragments landscapes—may lead to a higher number of species extinctions than predicted by the classical species–area relationship and thus approach a more nearly linear relationship (i.e., a relationship that predicts more rapid extinction).

We assumed no interactions between logging and poaching risk. Although the road networks associated with logging often increase poaching (20), there is also evidence of stronger enforcement in production forests (e.g., logging companies actively patrolling and protecting valuable resources) than in strict reserves (25, 26).

Econometric Analysis of Choice Experiment Responses. As explained in *Materials and Methods*, the willingness to pay (WTP) estimates used in Table 2 are derived from the results of the linear mixed logit model with correlated random coefficients in Table S4. The values of the means (95% confidence intervals) are US$1.08 (US$0.95, US$1.20) for protection against logging, US$0.71 (US$0.64, US$0.78) for protection against poaching, US$0.67 (US$0.59, US$0.74) for the maximum protection plan, and US$0.39 (US$0.28, US$0.51) for job creation. The 99% confidence intervals were only slightly wider: (US$0.91, US$1.25) for protection against logging, (US$0.62, US$0.80) for protection against poaching, (US$0.57, US$0.76) for the maximum protection plan, and (US$0.24, US$0.54) for job creation.

In looking at alternative models, simpler conditional logit and mixed logit models without correlated random parameters produced results that were qualitatively similar to those just described. The main difference with the conditional logit model was that the coefficients on the maximum protection plan and job creation were only significant at the 10% level. The random parameters specification allows heterogeneity in preferences and suggests that these characteristics of the alternatives are not important to some but not all respondents. Indeed, the distribution of preference parameters appears to be amenable to a lognormal assumption whereby the median respondent gets little extra utility from these aspects of a plan but some respondents care considerably about these aspects.

The model in Table S4 can be extended by entering squared terms for logging and poaching and an interaction term between logging and poaching all of which are significant at the 5% level. This model is shown in Table S5. This model suggests declining marginal utility for both logging and poaching protection over the range considered in our study, with protecting the second 150,000 ha from logging (poaching) being worth 89% (83%) of protecting the first 150,000 ha. Eventually this quadratic function turns negative at protection levels considerably larger than those considered in this study (~800,000 ha for logging and 500,000 ha for poaching, both of which exceed the total area of Belum–Temengor and thus are infeasible). The interaction term between hectares protected against logging and hectares protected against poaching is negative, suggesting that the two forms of protection are substitutes except for indicator variable for maximum protection, where the combination of the effects suggests that logging and poaching protection are much less substitutable.

Although the model in Table S5 provides a somewhat better fit to the data than the model in Table S4, we do not rely on it for our main estimates because our DCE design is not ideally suited for determining the curvature of the WTP function for the logging and poaching attributes. This is due in large part to the fact that our DCE has only three levels of logging and poaching, which span a limited (but realistic) range of protection possibilities. Three levels is the minimum needed to determine if there is any curvature associated with utility from these two attributes. The model in Table S5 clearly suggests curvature in the sense of declining marginal WTP, but the quadratic functional form used has the implausible implication that most of our sample would have a negative WTP for a much larger protection plan than the one considered here.

The standard alternative to a quadratic model for accommodating declining WTP is to specify attributes in terms of natural logs. The obvious difficulty for the logging and poaching attributes is that the status quo level for both of these attributes is zero, so we added 0.00001 (1 ha) to these attributes before taking logs and defined the interaction term using these two transformed variables. Qualitatively, results from this model were fairly similar to the quadratic model in Table S5 except that the status quo term was now insignificant. Examining implied WTP functions for increasing the number of hectares protected from logging and poaching suggests that WTP per hectare declines somewhat more sharply than it does in the quadratic model over the range considered. However, the value of the log-likelihood function is smaller (−3,710.4792) than for either the linear model in Table S4 or the quadratic model in Table S5.

We conclude from examining these different models that marginal WTP for logging and poaching protection appears to decline with the number of hectares protected, but that this effect is small enough within the range considered that the linear model in Table S4 is reasonable to use for the changes considered. Additional work would be needed to adequately characterize the nature of the curvature in the WTP functions.

3. Societal Cost of Protection

We based our cost estimate for expanding the number and coverage of warden patrols on a study by the Malaysian Economic Planning Unit and the Danish International Development Agency (27). That study estimated that the average amount of funding required for Malaysian protected areas to meet international management standards was US$12.39/ha$\cdot$y^{-1} (converted to 2010 prices using the Malaysian GDP deflator). It also estimated that the cost to meet the standards in South Africa was US$33.77/ha$\cdot$y^{-1}, which was the highest cost among the countries reviewed by the study. To be conservative, we used the latter estimate in Table 2, multiplying it by the 300,000-ha area of Belum–Temengor to arrive at the estimate of US$10.1 million/y.

In the absence of protection against logging, all of Belum–Temengor's 300,000 ha would be logged within 20 y, for an annual area harvested of 15,000 ha. Not all this area would be operable, however, due to steep slopes and restrictions on logging in riparian zones. The best available estimate of operable area in Belum–Temengor comes from the largest concession located within it, the Perak Integrated Timber Complex concession. The operable portion of this concession is 85.8%, which if applied to all of Belum–Temengor implies an annual area harvested of 12,870 ha. To estimate the annual opportunity cost of forgone logging, we needed to multiply this area by the per-hectare logging value.

The net economic contribution of logging is primarily stumpage value: the difference between logging revenue and logging cost, where cost includes a normal return to capital. (Consumer surpluses for processed wood products are likely small, as much of Malaysia's production of those products is exported into a competitive world market.) If the logging industry obtains timber harvest rights in a competitive manner, then stumpage value should equal the fees received by the forest owner for those rights. Under the Malaysian constitution, all forests are state owned. According to annual forestry statistics published by the Forestry Department Peninsular Malaysia, the sum of harvest fees in Perak in 2010 (royalties, premiums, cess) divided by the area harvested that year was US$867/ha. This amount could underestimate stumpage value, however, if timber harvest rights are not obtained competitively and the logging industry captured some of the stumpage value as windfall profits. The highest estimate of windfall profits in Peninsular Malaysia that we found in the literature indicated that harvest fees accounted for only

Example of show card for a choice set

	Policy A	Policy B	No protection
Logging	150,000 ha	0 ha	300,000 ha
	Half these species go extinct	None of these species go extinct	All these species go extinct
Poaching	0 ha	150,000 ha	300,000 ha
	None of these species go extinct	Half these species go extinct	All these species go extinct
Floods in Perak	3 per year	1 per year	5 per year
Jobs created in Perak	5,000	7,500	7,500
Cost to you	RM6 per month	RM6 per month	No cost

21.8% of stumpage value (28). This estimate dates from 1990, but we used it to be conservative and avoid understating the opportunity cost. (During the 1990s, many Malaysian states switched from administrative allocation of harvest rights to auctioning them, which increased the share of stumpage value captured by the government.) It implies that forgone stumpage value was US$3,976/ha. Multiplying this by 12,870 ha/y of harvested forest yields the value of US$51.2 million/y shown in Table 2.

We conservatively assumed that protection would not create any jobs, which means that 7,500 jobs would be forgone compared with the status quo. The associated opportunity cost was calculated in the same way as the societal benefits in Table 2, but using the WTP estimate for job creation from the linear mixed logit model with correlated random coefficients in Table S4 (US$0.39 per 100 jobs per month; section 2) instead of WTP for protection. The resulting total is US$6.4 million, as shown in Table 2. Note that this opportunity cost refers to the value respondents attach to job creation in Perak, not to the income associated with those jobs. Peninsular Malaysia has a low unemployment rate, and so any workers who were not recruited to work in the logging industry in Belum–Temengor would probably find other employment. The net loss to the Malaysian economy from the forgone 7,500 jobs would thus be negligible.

We also note that any job losses that resulted from protecting Belum–Temengor against logging or poaching would likely have no discernible effect on the labor market in the locations we surveyed in Selangor and Kuala Lumpur, given the distance between Belum–Temengor and those locations and the small size of the estimated number of forgone jobs (just 7,500) relative to the number of households in Selangor and Kuala Lumpur (nearly 2,000,000).

4. Overestimation of WTP Based on Stated Preferences

It is sometimes asserted that WTP estimates based on stated preferences (SPs) are overestimates. The evidence on this issue is mixed. Carson et al. (29) compared over 600 SP estimates to revealed-preference estimates in the form of actual behavior in situations where both types of estimates are available. They found that SP estimates tended on average to be somewhat smaller. This result was replicated in a recent metaanalysis (30) that focused solely on protection studies in the Asian/Pacific region. In a review of SP studies on a wide range of environmental goods and services in developing countries, Whittington (ref. 31, p. 222) found that WTP estimates are typically low, which was “not what most economists expected.” SP surveys that mimic a referendum scheduled to be held soon tend to produce a close correspondence to the actual referendum vote (32).

Laboratory experiments designed to obtained WTP estimates tend to find that purely hypothetical treatments produce overestimates, with a Murphy et al. (33) metaanalysis suggesting a median overestimate of 35%. Carson and Groves (34) show that purely hypothetical treatments do not have good incentive properties for truthful preference revelation, and they therefore recommend that survey designers emphasize the consequentiality of the SP results in terms of influencing policy decisions. This is the direction a number of recent papers have taken with good success (35, 36), and it is the direction we followed in our study.

A different issue with respect to possible overstatement arises when WTP estimates for protecting different areas are obtained under the typical assumption that each area is the only one being considered for protection by policymakers (37). Economic theory shows that the valuation estimate for a particular program should generally be falling in terms of the sequence order in which it is valued. The typical way economic valuation is done can be thought of valuing a program as if it were the first change to the current status quo being considered. Sequence effects must occur because households have less remaining income as they purchase goods in a sequence and those goods are to some degree substitutes for each other. As such, the summation of valuation estimates that are all obtained under the first-in-a-sequence assumption will produce an overestimate of the aggregate protection plan. The theoretical work of Carson et al. (38) suggests these sequence effects for nonmarketed goods are likely to be quite large.

Sequence effects are closely related to the issue of political agenda control and thus cannot be ignored when a series of programs is being considered. The fact that WTP to protect a subsequent forest might be lower than WTP to protect Belum–Temengor does not invalidate our estimate of WTP for the latter because Belum–Temengor has been at the top of the conservation agenda for conservation NGOs in Malaysia since the 1990s. Hence, there is a policy rationale for treating it as the first in a sequence.

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Table S1. Association of development with cross-country CIs that have data for multiple years

		Mean for indicated income group − Mean for UMI group				Per capita GNI	
Variable	Source	Sample	Low income	Lower-middle income	High income	Sample	Elasticity
Public opinion							
1 = protecting the environment should be given priority, 0 = economic growth and creating jobs should be the top priority	World Values Survey	54,058 household years; 29 countries, 3 survey waves: 1995–97, 1999–2002, 2005–2008	−0.276 (0.000)[b]	−0.116 (0.008)[b]	—	50,815 household years; 28 countries, 3 survey waves: 1995–97, 1999–2002, 2005–2008	0.745[a] (0.000)[b]
1 = environment is the most serious problem facing the country, 0 = other problems are more serious	AmericasBarometer	113,226 household years; 19 countries, 5 survey waves: 2004–2012, even years	−0.00797 (0.031)[b]	−0.00511 (0.148)[b]	—	101,039 household years; 17 countries, 5 y: 2004–2012, even years	5.32[a] (0.005)[b]
Domestic donations to WWF (constant 2005 US dollars per thousand people)	WWF country chapters[c]	42 country years; 5 countries, 2002–2012	−1.03 (0.084)[d]	−0.772 (0.174)[d]	—	42 country years; 5 countries, 2002–2012	5.64 (0.001)[d]
Percent cofinancing of GEF forest biodiversity projects	GEF	369 projects; 82 countries, 21 y: 1991–93, 1995–2012	−24.7 (0.002)	−12.0 (0.008)	—	324 projects; 62 countries, 21 y: 1991–93, 1995–2012	0.655 (0.002)
Percent land area in terrestrial protected areas	World Bank	2285 country years; 105 countries, 22 y: 1990–2010, 2012	−3.18 (0.000)	−1.94 (0.009)	2.48 (0.102)	1416 country years; 95 countries, 22 y: 1990–2010, 2012	0.311 (0.001)
Percent land area in forests protected for biodiversity conservation	FAO Forestry Department	361 country years; 95 countries, 4 y: 1990, 2000, 2005, 2010	−0.758 (0.080)	−0.418 (0.260)	0.110 (0.517)	254 country years; 89 countries, 4 y: 1990, 2000, 2005, 2010	0.189[e] (0.072)

For each indicator, results are shown for two regression models that included country fixed effects. Results for the first model (three center columns) give the difference between an indicator's mean when countries were in the low- or lower-middle-income group and its mean when countries were in the UMI group. Results for the second model (last two columns) show the association between an indicator and Per capita GNI, expressed as an elasticity. In that model, income was log-transformed, elasticities were calculated at means of the indicators, and, unless otherwise noted, indicators were log-transformed. *P* values for two-sided *t* tests of differences from zero are shown in parentheses next to the estimates; SEs were clustered by country unless otherwise noted. Samples included only tropical countries, as defined by the UN FAO Forestry Department (1), and are smaller in the second model due to incomplete income data. See section 1 for data sources.

[a]Used a logit model instead of a linear regression model.

[b]SEs clustered by country year.

[c]Brazil, India, Malaysia, Pakistan, and the Philippines.

[d]Newey–West SEs instead of clustered SEs, due to the small number of countries.

[e]The dependent variable was not log-transformed, as it included values of zero.

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Table S2. Association of development with cross-country CIs that have data for a single time period

		Mean for indicated income group − Mean for UMI group[a]				Per capita GNI	
Variable	Source	Sample	Low income	Lower-middle income	High income	Sample	Elasticity
Public opinion 1 = loss of plant or animal species or biodiversity is a very serious environmental problem in the world as a whole, 0 = this loss is somewhat serious, not very serious, or not serious at all	World Values Survey	21,312 household years; 15 countries, 1 survey wave: 2005–2008	−0.0720 (0.000)	−0.278 (0.000)	0.142 (0.000)	19,896 household years; 14 countries, 1 survey wave: 2005–2008	0.204[a] (0.000)
No. of environmental NGOs per million people	Environmental Encyclopedia and Directory	106 countries; year = 2005	−15.1 (0.046)	−13.2 (0.082)	−3.69 (0.684)	98 countries; year = 2005	0.809 (0.000)
Domestic budget for protected areas (thousand 2005 US dollars per kilometer squared)	James et al. (1), Mansourian and Dudley (2)	79 countries; year varies; 1990–2007	−9.76 (0.075)	−9.47 (0.097)	23.1 (0.302)	56 countries; year varies, 1990–2007	0.810[b] (0.000)
Domestic conservation spending (2005 US dollars per capita)	Waldron et al. (3)	87 countries; mean, 2001–2008	−2.47 (0.003)	−2.07 (0.019)	8.18 (0.300)	85 countries; mean, 2001–2008	1.03 (0.000)
Domestic conservation spending (percent of total)	Waldron et al. (3)	85 countries; mean, 2001–2008	−29.7 (0.002)	−31.7 (0.002)	27.7 (0.001)	84 countries; mean, 2001–2008)	0.368 (0.001)
Domestic public expenditures on forestry (percent of total)	FAO Forestry Department	44 countries; year = 2005	−37.8 (0.000)	−23.0 (0.002)	0.032 (0.925)	43 countries; year = 2005	0.240 (0.019)

For each indicator, results are shown for two regression models. Results for the first model (four center columns) give the difference between an indicator's mean when countries were in the low- or lower-middle-income group and its mean when countries were in the UMI group. Results for the second model (last two columns) show the association between an indicator and per capita GNI, expressed as an elasticity. In that model, income was log-transformed, elasticities were calculated at means of the indicators, and, unless otherwise noted, indicators were not log-transformed, due to observations equaling zero. *P* values for two-sided *t* tests of differences from zero are shown in parentheses next to the estimates, based on nonclustered robust SEs. Samples included only tropical countries, as defined by the UN FAO Forestry Department (4), and are smaller in the second model due to incomplete income data. See section 1 for data sources.

[a]Used a logit model instead of a linear regression model.

[b]The dependent variable was log-transformed.

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Table S3. Effects of respondent characteristics on WTP to protect 100,000 ha of Belum–Temengor against logging or poaching

	Protection against logging		Protection against poaching	
Variables	Income groups	Income splines	Income groups	Income splines
Income				
RM0	0.0566		0.462	
	(0.982)		(0.686)	
RM1–1,500	0.830*		0.426	
	(0.0893)		(0.115)	
RM3,001–5,000	0.602		0.439	
	(0.275)		(0.157)	
RM5,001–7,500	0.974		0.579	
	(0.136)		(0.126)	
RM7,501–10,000	1.960***		1.297***	
	(0.00890)		(0.00165)	
RM10,001–13,000	3.159***		1.964***	
	(0.00111)		(0.000155)	
RM13,001–16,000	0.218		0.570	
	(0.877)		(0.392)	
RM16,001–20,000	1.800		0.848	
	(0.299)		(0.458)	
>RM20,000	3.653**		2.458**	
	(0.0243)		(0.0302)	
Lower spline		0.128		0.0757
		(0.245)		(0.162)
Upper spline		0.118**		0.0798**
		(0.0354)		(0.0288)
Age	−0.149	−0.141	−0.0496	−0.0525
	(0.173)	(0.123)	(0.400)	(0.289)
Age squared	0.00143	0.00135	0.000370	0.000417
	(0.290)	(0.236)	(0.616)	(0.506)
Education				
Primary	−0.0560	0.0896	−0.0206	0.0321
	(0.943)	(0.910)	(0.966)	(0.946)
Tertiary	−0.454	−0.323	−0.331	−0.202
	(0.307)	(0.461)	(0.222)	(0.454)
Stratum				
Kuala Lumpur	−0.114	−0.0954	−0.0103	0.0208
	(0.792)	(0.825)	(0.965)	(0.930)
Selangor, urban	−0.176	−0.291	0.0359	−0.0154
	(0.648)	(0.456)	(0.871)	(0.944)
Ethnicity				
Chinese	−1.766***	−1.800***	−0.978***	−0.967***
	(0.000821)	(0.00114)	(0.000608)	(0.000782)
Indian	−0.859**	−0.736*	−0.477**	−0.410*
	(0.0436)	(0.0932)	(0.0468)	(0.0964)
Household size	−0.0538	−0.0593	−0.0255	−0.0311
	(0.596)	(0.573)	(0.626)	(0.572)
Constant	7.427***	7.493***	3.740***	3.925***
	(0.000685)	(2.33e-05)	(0.00125)	(5.74e-05)
F statistic (*P* value)	2.34 (0.0024)	2.64 (0.0036)	2.45 (0.0015)	2.64 (0.0037)
R^2	0.053	0.042	0.054	0.043
Observations	1,259	1,259	1,259	1,259

Table shows parameter estimates for covariates in multiple regression models of household WTP to protect Belum–Temengor (ordinary least-squares with complex survey weights). Each column is a separate regression model: two each for protection against logging and poaching. *P* values are shown in parentheses below the parameter estimates; asterisks indicate significance at 1% (***), 5% (**), and 10% (*). All covariates are dummy variables except respondent age (years), household size (number), and income splines (Malaysian ringgit per month, based on midpoints of ranges in income groups; knot at RM6,250.50). Excluded dummies: income group, RM1,501–3,000; education, secondary; stratum, rural Selangor; and ethnicity, Bumiputera. Adjusted Wald tests indicated that the coefficients on Age and Age-squared were jointly significantly different from zero in the four models (left to right) at $P < 0.087$, $P < 0.074$, $P < 0.095$, and $P < 0.096$.

Table S4. Mixed logit results: Linear model with correlated random coefficients

Variable	Coefficient	SE	z	$P > \lvert z \rvert$	95% confidence interval	
Results of Stata mixlogit command[a]						
LogHectProt	1.422649	0.1099519	12.94	0	1.207147	1.638151
PoachHectProt	0.9282407	0.0821303	11.3	0	0.7672683	1.089213
JobsCreate	0.0434093	0.0207744	2.09	0.037	0.0026922	0.0841265
StatusQuo	−2.979154	0.4547458	−6.55	0	−3.87044	−2.087869
MaxPlan	0.5453521	0.2585582	2.11	0.035	0.0385874	1.052117
mPrice	−1.580052	0.1261867	−12.52	0	−1.827373	−1.332731
/l11	1.18249	0.1040417	11.37	0	0.978572	1.386408
/l21	0.6438382	0.0711596	9.05	0	0.504368	0.7833084
/l31	0.0739531	0.0282598	2.62	0.009	0.018565	0.1293413
/l41	1.597613	0.4624652	3.45	0.001	0.6911982	2.504028
/l51	0.2933554	0.2884871	1.02	0.309	−0.2720689	0.8587798
/l61	0.9891639	0.0732167	13.51	0	0.8456618	1.132666
/l22	0.3389351	0.0705517	4.8	0	0.2006562	0.477214
/l32	−0.0279666	0.037976	−0.74	0.461	−0.1023981	0.046465
/l42	2.001943	0.3450693	5.8	0	1.325619	2.678266
/l52	0.155654	0.3928866	0.4	0.692	−0.6143896	0.9256975
/l62	0.5570772	0.0620563	8.98	0	0.4354491	0.6787053
/l33	−0.0768994	0.0431149	−1.78	0.074	−0.1614031	0.0076043
/l43	3.266841	0.4784315	6.83	0	2.329133	4.20455
/l53	−0.2129923	0.3093126	−0.69	0.491	−0.8192338	0.3932493
/l63	0.6883687	0.0858632	8.02	0	0.5200799	0.8566575
/l44	3.815815	0.3455714	11.04	0	3.138507	4.493122
/l54	0.495337	0.3442337	1.44	0.15	−0.1793486	1.170023
/l64	−0.929683	0.0557744	−16.67	0	−1.038999	−0.8203672
/l55	−0.5747781	0.4472355	−1.29	0.199	−1.451343	0.3017873
/l65	0.0474174	0.0532585	0.89	0.373	−0.0569674	0.1518022
/l66	−0.0831935	0.0447923	−1.86	0.063	−0.1709848	0.0045979
Results of Stata mixlcov, sd command[b]						
LogHectProt	1.18249	0.1040417	11.37	0	0.978572	1.386408
PoachHectProt	0.727602	0.0774071	9.4	0	0.5758869	0.8793171
JobsCreate	0.1102937	0.0309453	3.56	0	0.049642	0.1709455
StatusQuo	5.638514	0.5375521	10.49	0	4.584931	6.692096
MaxPlan	0.8552075	0.3583881	2.39	0.017	0.1527797	1.557635
mPrice	1.623611	0.0770259	21.08	0	1.472643	1.774579
Results of Stata mixlcov command[c]						
v11	1.398283	0.2460566	5.68	0	0.9160206	1.880545
v21	0.7613322	0.134142	5.68	0	0.4984188	1.024246
v31	0.0874488	0.0340687	2.57	0.01	0.0206754	0.1542223
v41	1.889162	0.6043324	3.13	0.002	0.704692	3.073632
v51	0.3468899	0.3335037	1.04	0.298	−0.3067654	1.000545
v61	1.169676	0.1464519	7.99	0	0.8826359	1.456717
v22	0.5294046	0.1126431	4.7	0	0.3086282	0.750181
v32	0.038135	0.021376	1.78	0.074	−0.0037612	0.0800312
v42	1.707133	0.4115825	4.15	0	0.9004462	2.51382
v52	0.24163	0.2268881	1.06	0.287	−0.2030625	0.6863226
v62	0.8256745	0.1220111	6.77	0	0.5865371	1.064812
v33	0.0121647	0.0068262	1.78	0.075	−0.0012143	0.0255437
v43	−0.1890571	0.1464702	−1.29	0.197	−0.4761335	0.0980193
v53	0.0337204	0.0363166	0.93	0.353	−0.0374589	0.1048997
v63	0.0046371	0.0403285	0.11	0.908	−0.0744053	0.0836795
v44	31.79284	6.06199	5.24	0	19.91156	43.67412
v54	1.974581	1.380839	1.43	0.153	−0.7318133	4.680976
v64	1.396831	0.5499836	2.54	0.011	0.3188831	2.474779
v55	0.7313799	0.6129924	1.19	0.233	−0.4700632	1.932823
v65	−0.2574902	0.5376067	−0.48	0.632	−1.31118	0.7961995
v66	2.636112	0.2501201	10.54	0	2.145885	3.126338

[a]Variable definitions: LogHectProt, area protected against logging (hectare); PoachHectProt, area protected against poaching (hectare); JobsCreate, jobs created; StatusQuo, dummy variable for the status quo alternative; MaxPlan, dummy variable for maximum protection (all 300,000 ha protected against both logging and poaching); mPrice, negative of the cost of the plan (Malaysian ringgit per month). Additional parameters are from the log-likelihood function and are related to the SD of the random components for attributes and the covariance matrix of attribute parameters. SEs are clustered by enumeration block (203 clusters). Log-likelihood = −3,592.8423, Wald $\chi^2(1)$ = 809.16 (P < 0.0001), observations = 15,120.

[b]SDs of random components associated with attributes shown in "Results of Stata mixlcov, sd command."

[c]Elements in the coefficient covariance matrix for the model shown in "Results of Stata mixlcov command."

Table S5. Mixed logit results: Model with squared and interaction terms

Variable	Coefficient	SE	z	$P > \|z\|$	95% confidence interval	
			Results of Stata mixlogit command[a]			
LogHectProt	2.264429	0.3076641	7.36	0	1.661418	2.867439
Logging2	−0.147292	0.0616883	−2.39	0.017	−0.2681989	−0.0263851
PoachHectProt	1.799159	0.2977147	6.04	0	1.215648	2.382669
Poaching2	−0.1709216	0.0680542	−2.51	0.012	−0.3043054	−0.0375378
LogPoach	−0.1974902	0.0727092	−2.72	0.007	−0.3399976	−0.0549828
MaxPlan	1.31426	0.3987912	3.3	0.001	0.5326441	2.095877
StatusQuo	−2.098039	0.5523284	−3.8	0	−3.180583	−1.015496
JobsCreate	0.0519419	0.0250331	2.07	0.038	0.0028779	0.1010059
mPrice	−1.523467	0.158112	−9.64	0	−1.833361	−1.213573
/l11	−2.514799	0.4392547	−5.73	0	−3.375722	−1.653876
/l21	0.4107209	0.113206	3.63	0	0.1888413	0.6326005
/l31	−0.8569122	0.4423506	−1.94	0.053	−1.723903	0.0100791
/l41	0.0168343	0.1514287	0.11	0.911	−0.2799604	0.3136291
/l51	0.1462789	0.0968452	1.51	0.131	−0.0435341	0.336092
/l61	−1.01092	0.6268586	−1.61	0.107	−2.23954	0.2177005
/l71	−3.021665	0.4875641	−6.2	0	−3.977273	−2.066057
/l81	−0.0272195	0.0284277	−0.96	0.338	−0.0829368	0.0284978
/l91	−0.9150466	0.0694335	−13.18	0	−1.051134	−0.7789595
/l22	−0.313595	0.0569406	−5.51	0	−0.4251966	−0.2019935
/l32	−0.3974566	0.5720511	−0.69	0.487	−1.518656	0.7237429
/l42	−0.0720436	0.1688018	−0.43	0.67	−0.402889	0.2588018
/l52	0.1591533	0.1231254	1.29	0.196	−0.082168	0.4004747
/l62	0.0646308	0.7835937	0.08	0.934	−1.471185	1.600446
/l72	−1.254742	0.3927499	−3.19	0.001	−2.024518	−0.4849667
/l82	−0.0820833	0.0345067	−2.38	0.017	−0.1497151	−0.0144515
/l92	−0.6921576	0.0915779	−7.56	0	−0.8716469	−0.5126682
/l33	−0.9132879	0.4952244	−1.84	0.065	−1.88391	0.057334
/l43	0.1302098	0.1545607	0.84	0.4	−0.1727236	0.4331432
/l53	0.1929936	0.1049452	1.84	0.066	−0.0126953	0.3986825
/l63	−0.6542424	0.6756219	−0.97	0.333	−1.978437	0.6699522
/l73	−4.553715	0.7712997	−5.9	0	−6.065434	−3.041995
/l83	0.0522685	0.0370992	1.41	0.159	−0.0204446	0.1249815
/l93	0.034682	0.0542489	0.64	0.523	−0.071644	0.1410079
/l44	0.0137584	0.03849	0.36	0.721	−0.0616807	0.0891974
/l54	0.0669006	0.1208223	0.55	0.58	−0.1699067	0.303708
/l64	−0.1378344	0.8148219	−0.17	0.866	−1.734856	1.459187
/l74	1.101916	0.6395711	1.72	0.085	−0.1516204	2.355452
/l84	−0.0727075	0.0454021	−1.6	0.109	−0.1616939	0.0162789
/l94	0.0469185	0.0771021	0.61	0.543	−0.1041988	0.1980358
/l55	−0.0963138	0.1304545	−0.74	0.46	−0.3519999	0.1593722
/l65	1.009268	1.394089	0.72	0.469	−1.723097	3.741633
/l75	1.374268	1.313254	1.05	0.295	−1.199661	3.948198
/l85	−0.0592146	0.0368021	−1.61	0.108	−0.1313453	0.012916
/l95	−0.0341919	0.108332	−0.32	0.752	−0.2465188	0.1781349
/l66	0.7150076	0.3230769	2.21	0.027	0.0817885	1.348227
/l76	3.348824	0.4129348	8.11	0	2.539487	4.158162
/l86	0.0645787	0.0326689	1.98	0.048	0.0005489	0.1286085
/l96	−0.8313455	0.0972514	−8.55	0	−1.021955	−0.6407363
/l77	2.956036	0.9259074	3.19	0.001	1.14129	4.770781
/l87	−0.0624367	0.0381887	−1.63	0.102	−0.1372852	0.0124118
/l97	0.6593615	0.1318837	5	0	0.4008743	0.9178488
/l88	0.0247099	0.0444822	0.56	0.579	−0.0624735	0.1118934
/l98	0.2270851	0.0410439	5.53	0	0.1466405	0.3075296
/l99	−0.0493442	0.0404294	−1.22	0.222	−0.1285844	0.0298959
			Results of Stata mixlcov, sd command[b]			
LogHectProt	2.514799	0.4392547	5.73	0	1.653876	3.375722
Logging2	0.5167528	0.1076567	4.8	0	0.3057496	0.727756
PoachHectProt	1.313912	0.4752345	2.76	0.006	0.3824697	2.245355
Poaching2	0.1503913	0.1124367	1.34	0.181	−0.0699805	0.3707631
LogPoach	0.3126114	0.1267352	2.47	0.014	0.0642149	0.5610079
MaxPlan	1.732924	0.9136544	1.9	0.058	−0.0578058	3.523654
StatusQuo	7.382192	0.6715934	10.99	0	6.065893	8.698491

Table S5. Cont.

Variable	Coefficient	SE	z	$P > \|z\|$	95% confidence interval	
JobsCreate	0.166381	0.0299781	5.55	0	0.1076251	0.2251369
mPrice	1.581411	0.1718941	9.2	0	1.244505	1.918317
		Results of Stata mixlcov command[c]				
v11	6.324214	2.209274	2.86	0.004	1.994116	10.65431
v21	−1.03288	0.4600991	−2.24	0.025	−1.934658	−0.1311027
v31	2.154962	1.253051	1.72	0.085	−0.3009727	4.610896
v41	−0.042335	0.3814017	−0.11	0.912	−0.7898686	0.7051986
v51	−0.3678621	0.2906007	−1.27	0.206	−0.9374291	0.2017049
v61	2.54226	1.894798	1.34	0.18	−1.171475	6.255995
v71	7.598879	2.111123	3.6	0	3.461153	11.7366
v81	0.0684515	0.0746386	0.92	0.359	−0.0778374	0.2147404
v91	2.301158	0.4471503	5.15	0	1.42476	3.177557
v22	0.2670335	0.1112638	2.4	0.016	0.0489605	0.4851064
v32	−0.2273113	0.327476	−0.69	0.488	−0.8691525	0.4145299
v42	0.0295067	0.1010837	0.29	0.77	−0.1686137	0.2276271
v52	0.0101701	0.0639072	0.16	0.874	−0.1150858	0.135426
v62	−0.4354737	0.4576837	−0.95	0.341	−1.332517	0.4615699
v72	−0.8475798	0.3797183	−2.23	0.026	−1.591814	−0.1033456
v82	0.0145613	0.0162151	0.9	0.369	−0.0172196	0.0463422
v92	−0.1587716	0.100498	−1.58	0.114	−0.355744	0.0382008
v33	1.726365	1.248833	1.38	0.167	−0.7213019	4.174032
v43	−0.1047104	0.2095033	−0.5	0.617	−0.5153293	0.3059085
v53	−0.3648635	0.310991	−1.17	0.241	−0.9743947	0.2446678
v63	1.438093	1.289447	1.12	0.265	−1.089176	3.965362
v73	7.246859	3.16999	2.29	0.022	1.033793	13.45993
v83	0.0082131	0.0609993	0.13	0.893	−0.1113434	0.1277696
v93	1.027543	0.4081309	2.52	0.012	0.2276206	1.827464
v44	0.0226176	0.033819	0.67	0.504	−0.0436665	0.0889016
v54	0.0170466	0.0499129	0.34	0.733	−0.0807808	0.1148741
v64	−0.1087595	0.2240311	−0.49	0.627	−0.5478524	0.3303334
v74	−0.5382492	0.7651699	−0.7	0.482	−2.037955	0.9614562
v84	0.0112609	0.0115197	0.98	0.328	−0.0113173	0.0338391
v94	0.0396228	0.1167829	0.34	0.734	−0.1892676	0.2685131
v55	0.0977259	0.0792378	1.23	0.217	−0.0575773	0.253029
v65	−0.3702823	0.3686997	−1	0.315	−1.092921	0.3523558
v75	−1.579182	0.7683656	−2.06	0.04	−3.085151	−0.0732132
v85	−0.006119	0.020647	−0.3	0.767	−0.0465863	0.0343483
v95	−0.2308858	0.1196459	−1.93	0.054	−0.4653875	0.0036159
v66	3.003025	3.166587	0.95	0.343	−3.203372	9.209422
v76	9.582357	4.275099	2.24	0.025	1.203318	17.9614
v86	−0.0155522	0.1525298	−0.1	0.919	−0.3145052	0.2834008
v96	0.2222194	0.6228617	0.36	0.721	−0.998567	1.443006
v77	54.49676	9.915662	5.5	0	35.06242	73.9311
v87	−0.1825711	0.2468245	−0.74	0.459	−0.6663381	0.301196
v97	2.645289	0.9523871	2.78	0.005	0.7786445	4.511933
v88	0.0276826	0.0099756	2.78	0.006	0.0081309	0.0472344
v98	−0.0070965	0.0595334	−0.12	0.905	−0.1237799	0.1095868
v99	2.500861	0.5436704	4.6	0	1.435287	3.566436

[a]Variable definitions are as in Table S4 except Logging2 (LogHectProt squared), Poaching2 (PoachHectProt squared), and LogPoach (LogHectProt × PoachHectProt). SEs are clustered by enumeration block (203 clusters). Log-likelihood = −3,570.5258, Wald $\chi^2(1) = 425.59$ ($P < 0.0001$), observations = 15,120.
[b]SDs of random components associated with attributes shown in "Results of Stata mixlogit command."
[c]Elements in the coefficient covariance matrix for the model shown in "Results of Stata mixlogit command."