UNIVERSITY OF WAIKATO

Hamilton
New Zealand

Forest Loss and Economic Inequality in the Solomon Islands: Using Small-Area Estimation to Link Environmental Change to Welfare Outcomes

John Gibson

Department of Economics

Working Paper in Economics 14/17

July 2017

John Gibson

Department of Economics
University of Waikato
Private Bag 3105
Hamilton
New Zealand, 3240

Tel: +64 (7) 838 4289

Fax: +64 (7) 838 4331

Email: jkgibson@waikato.ac.nz

Abstract

To study welfare effects of environmental change, data from household surveys may be linked to remote sensing data. If linking uses spatial aggregation there is risk of ecological fallacy, since surveys are only representative for large areas that may not correspond to the spatial scale of the decision-making units. This paper uses survey-to-census imputation to estimate welfare indicators for small areas in order to study the effect of deforestation on subsequent inequality in the rural Solomon Islands. This country depends on logging for almost half of foreign exchange and one-sixth of government revenue, and most forested land remains under customary ownership. A sharp increase in log exports, to seven times the sustainable yield, and a major shift in export destinations as other countries withdrew from the tropical log trade represents an exogenous shock that helps to identify effects of deforestation on inequality rather than the reverse relationship. Using data for rural wards, that have about 400 households each, a standard deviation increase in the rate of forest loss over 2000 to 2012 raises the Gini index for household consumption in 2013 by one-third of a standard deviation. This precisely estimated effect would not be apparent using more spatially aggregated data.

Keywords

deforestation
inequality
poverty
small-area estimation

JEL Codes

O15, Q23

Acknowledgements

I am grateful to the World Bank for support with data and funding for the small area estimation, to Steve Hoskins for research assistance, to Geua Boe-Gibson for the preparation of the maps and to participants at the Association for Environmental and Resource Economics conference for helpful comments. The views expressed here are those of the author alone.

1. Introduction

The human causes of deforestation are widely studied but the consequences for humans rather less so.[1] Instead, human causes and environmental consequences are the two most widely researched themes. One reason for this asymmetry may be that deforestation can affect people in different times and places from where it occurs, given the role of forests in the global carbon cycle. At this temporal and spatial scale, linking environmental change to a narrow indicator of human welfare for a defined group can be difficult. Yet, absent such evidence, policy makers may see immediate economic benefits, like export revenues and royalties from logging, but not have enough information on immediate welfare costs to balance them, especially if costs to the environment are downplayed as something for future policy makers to deal with.

This paper presents evidence on one particular welfare cost of forest loss, which is that there is higher local economic inequality within affected communities. There are at least two pathways through which such an effect could occur. First, the windfall from natural resource exploitation can exacerbate rent-seeking conflict, creating winners and losers in a society. This may be especially likely with customary (tribal) ownership, since without clearly delineated property rights there can be conflict over who gets what. While most evidence on the link from resource exploitation to conflict is from cross-country studies, supportive evidence for this channel is also emerging from within-country studies (Aragón *et al.* 2015). Second, the poor rely more on forests for food, fodder and fuel than do the non-poor, and so forests have a strong equalizing effect on the local income distribution (Vedeld *et al.* 2007). When this source of environmental income is disrupted it will tend to exacerbate local inequality.

While the pathways from forest loss to inequality are intuitively plausible, they remain largely unstudied, perhaps because of the well-known problem of linking people to pixels (Geoghegan *et al.* 1998). Data on inequality and welfare are mostly from household surveys while environmental change is typically measured by remote sensing. If these two types of data are matched by using spatial aggregation there is risk of an ecological fallacy; most surveys are only representative for large areas, such as a province, that does not match the land-owning unit making decisions about forests. Moreover, aggregating to a larger area to get enough observations for calculating inequality statistics runs the risk of smoothing a lot of intra-unit spatial variability and may introduce spatial autocorrelation (Anselin 2001).[2]

[1] A small literature considers effects of deforestation on human health. There is evidence that forest loss increases the local incidence of malaria in Indonesia (Garg 2016) and in Nigeria (Berazneva and Byker 2017).

[2] If pixels are small, and if surveyed households (or clusters of them, such as a particular point in an enumeration area) are geo-referenced, then buffers can be created around each household or cluster and measurements of forest change made for all pixels within the buffer (for example, this is used by Berazneva and Byker 2017). However, the size of the buffer is often *ad hoc* and may not match with the scale of decision-making units.

A technique that has proved useful in development economics, but is rarely applied in environmental economics, is small-area estimation with survey-to-census imputation.[3] Survey data are used to estimate a model of consumption, with explanatory variables restricted to those with overlapping distributions available from a recent census. Coefficients from this model are combined with variables from the census, to predict consumption for each census household. The models are designed to reduce common location terms in residuals so that predictions are more precise, and simulations draw from idiosyncratic and correlated components of the errors (Elbers *et al.* 2003). The repeated simulations are then used to calculate welfare indicators with a high degree of precision for small areas. Most applications of the method focus on poverty but it can also measure inequality for smaller areas than is possible with a survey. For example, Demombynes and Özler (2005) created inequality statistics for police precincts in South Africa (n=1064) to match to crime rate data available at the same spatially disaggregated level.

This paper studies the effect of forest loss from 2000 to 2012 on the subsequent level of economic inequality, at ward level for the rural Solomon Islands. Wards are the sub-national unit below provinces, and the median rural ward has just 360 households, which is far smaller than the typical survey domains for which inequality is reported. The inequality estimates produced by the survey-to-census imputation allow an area-to-area matching of remote sensing and welfare data that is particularly suitable when resource management decisions are made by collective entities, such as tribes. In the Solomon Islands, 90% of the forested land is under customary (tribal) ownership. Landowners get royalties from logging companies (equivalent to about 15% of free-on-board log prices) and also may be compensated if roads have to be built on their land so as to access forest stands. In some cases, community leaders may be paid by the companies to facilitate negotiations over logging concession.

Although wards are political and statistical units, they match well with patterns of tribal control over land. It is the customary landowners (or some subset of them) who grant logging concessions so the pattern of deforestation also tends to have spatial patterns that vary by ward. Typically, tribal boundaries extend inland from the coast to the mountainous spine of each of the main islands. The lack of existing roads, and the easy access from the sea also means that logging follows a similar spatial pattern. Indeed, the forests in the Solomon Islands are highly accessible, compared to other forested islands in Asia-Pacific, because islands are close to each other so a foreign logging company can quickly move from one site to another, and can service several sites with the same mother ships (Katovai *et al.* 2015).

The accessibility of forests and the limited scope of other economic activities makes the Solomon Islands highly dependent on logging. Almost 50% of foreign exchange and 17% of government revenue come from logging (URS, 2014). There is little chance of logging

[3] Sims (2010) studies the effect of protected areas in Thailand on local poverty, with the small-area estimation method used here.

being replaced with plantation forestry; plantations are just one percent of the area of indigenous forests (Pauku 2009). Likewise, sawn timber exports – often from indigenous companies rather than multinationals – are only 5% of the value of log exports (URS, 2014). Thus, policy makers may see current economic benefits from logging while the environmental costs are discounted as falling more on future generations. This may be especially so in the Solomon Islands, which remains highly forested even though the value of the forest resource is being rapidly depleted. In such a setting, a more complete evaluation may be possible if some of the current welfare costs of logging – which may include higher inequality – are highlighted.

While the effect of forest loss on inequality is largely unstudied, there is literature on the reverse relationship, of inequality causing environmental degradation.[4] For example, Boyce (1994) claims that inequalities of power and wealth lead to more environmental degradation, since the extent to which an environmentally degrading activity is carried out depends on the balance of power between those who benefit from the activity and those who bear the cost of the degradation. Torras and Boyce (1998) found corroborating evidence in cross-country data, with greater income inequality associated with more pollution. A related study by Koop and Tole (2001) found that countries with high levels of inequality in either income or land ownership saw economic development associated with more deforestation, while in more equal countries there was less deforestation as the country grew richer.

While cross-country studies predominate in the literature on the effects of inequality on environmental damage,[5] if the same relationship were to hold at the micro level it may make it hard to untangle effects of deforestation on inequality from the reverse relationship. One favourable feature for a causal interpretation of how deforestation from 2000 to 2012 impacted inequality in 2013 is the dramatic shift in the volume and profile of log exports from the Solomon Islands. Since 2001, export volumes grew at an annual rate of 11.4% (s.e. 1.2%), with no significant time trend immediately prior to then. The driving force behind this growth has been exports to China, which have an annual growth rate of 23.3% (s.e. 4.2%). China has gone from being the destination for just 13% of Solomon Islands log exports in 2001 to now taking 95% of these exports. At the same time, the Solomon Islands has become the second largest source of tropical log imports for China. These shifts in export destinations for Solomon Islands logs and import sources for China are likely driven by other countries withdrawing from the trade in tropical logs, and so this represents an exogenous change for the Solomon Islands.

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[4] These are just a small component of the broader literature that considers how environmental degradation varies with economic development. For example, only 2.7% of regressions used to study the environmental Kuznets curve for deforestation include an inequality variable, in the meta-analysis by Choumert *et al.* (2013).

[5] Cushing *et al.* (2015) review almost 100 studies and find the only within-country ones are for the United States.

The remainder of the paper is structured as follows: Section 2 describes the setting, Section 3 covers how the main measures of deforestation and inequality are derived, Section 4 reports the results, and Section 5 concludes.

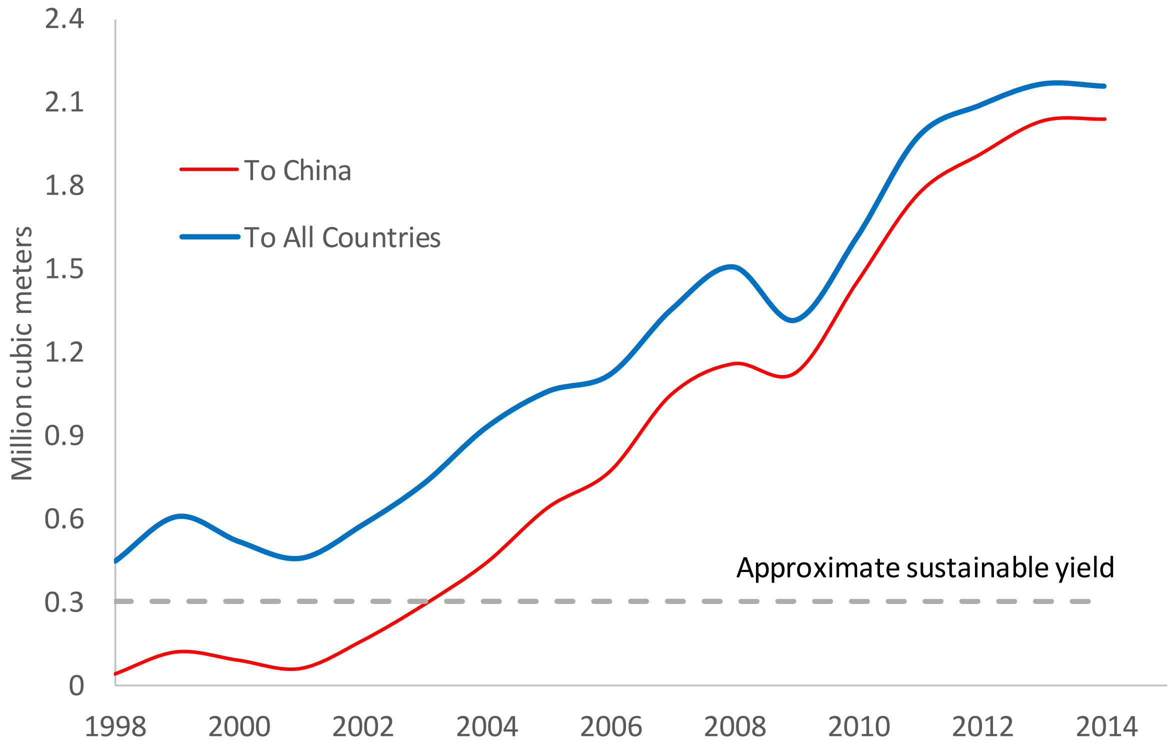
2. Background and Context

The Solomon Islands are a group of tropical oceanic islands, northeast of Australia. There are approximately 1000 islands in the country, although many are very small. The total land area is about two-thirds larger than Hawaii, and the largest individual islands are about the size of Delaware, in the United States. The larger islands are intersected by deep, narrow valleys, and obtain highest point elevations of between 1000 to 2000 meters. Typically the mountainous spine of each of the main islands acts as a boundary to tribal lands, which extend inland from the coast. The boundaries for wards also tend to follow a similar topography. The islands are covered by tropical rainforest, often classified as hill forests that occur at altitudes from 400-600 meters, with varying tree heights and canopy density (Pauku 2009).

Large-scale commercial logging in the Solomon Islands started over 50 years ago, on the small amount of alienated government land. However, beginning in the 1980s, logging by multinational companies shifted to customary land, which is five-sixths of all land and 90% of forested areas (GoSI, 2010). The *Forest Resources and Timber Utilization Act* governs the process by which a logging concession is granted; the provincial government (there are nine) identifies which of the landowners in a group can grant timber rights to a concessionaire. This can lead to a form of elite-capture, where politicians and tribal 'big men' make deals with foreign loggers while some community members miss out (Katovai *et al.* 2015). The coalition between logging companies, politicians, and tribal elites may also facilitate illegal logging and other deviations from agreements since few ordinary people are willing to oppose these elite groups by undertaking legal efforts to enforce safeguard provisions (Hughes 2010). This timber rights process is also claimed to create an unfair division of benefits, that causes internal conflict and leads to increasing inequality within rural landowner groups (Corrin 2012).

The logging that is practiced in the Solomon Islands is meant to be selective, where a focus on high-value species and cut-size limitations could provide a sustainable yield. In fact, there is considerable forest degradation due to poorly enforced selective logging (Katovai *et al.* 2015). The current rate of log exports is approximately seven times the sustainable level, noting that the estimates of the sustainable yield for national log harvests vary from 0.25 million m^3 per year (Hughes 2010) to 0.3 million m^3 (URS, 2014). Prior to 2001, log exports were about 50% above the sustainable yield, fluctuating between about 0.4 and 0.6 million m^3, but since then the rapid growth in exports to China has seen exports expand to over 2.1 million m^3 (Figure 1).[6] As noted above, this sharp increase in total exports, and the change in export destination, likely reflects the withdrawal of other countries from the tropical log trade. This exogenous shock to the Solomon Islands helps to identify the effects of deforestation on inequality rather than the reverse relationship.

Figure 1: Trends in Log Exports from the Solomon Islands



Note: Data are from the import statistics of importers, due to concerns about under-invoicing of exports.

Previous research from the Solomon Islands notes that forests with less than 30-40% crown cover produce less than $20m^3$ of commercial timber per hectare, which makes them less economically attractive for logging (Jansen *et al.* 2006). Thus, even if there was properly controlled selective logging, the decline in the economic value of the forest due to the stand-replacing disturbance may be greater than would be indicated by just focusing on felling rates. Moreover, when selective logging is not controlled, harvest intensities may be three times higher than they should be, at about 30 cut trees per hectare, and at this cutting rate a residual stand of severely damaged immature trees is left behind (Katovai *et al.* 2015). Along these lines, a recent forest resource assessment for the Solomon Islands found more than half of the primary commercial forest resource has now been exploited (SKM, 2012).

[6] There may be under-invoicing of log exports (see www.globaltimber.org.uk/solomonislands.htm for details). Therefore, the data in Figure 1 are from import statistics for China and the other main importers (Japan, South Korea, the Philippines) and from UN Comtrade data, which may be more reliable than the export statistics for the Solomon Islands.

Regenerative potential of the remaining forest is also harmed by re-entry logging, which is made possible because of poor monitoring and possibly because of lack of information on the environmental and economic effects of the existing logging – without this information the costs and benefits of letting loggers back into an area cannot be properly appraised (Katovai *et al.* 2015).

While most research on forests in the Solomon Islands is on logging, the forests are also an important source of food, especially for the rural poor. The Solomon Islands has a number of indigenous nut tree species, and especially the Ngali nut which grows on large trees (ca. 40 meter height) of the *Canarium* species. A mature tree can provide up to 30 kilograms of nuts per year, which are harvested from the forest floor and are eaten both fresh and dried. This is a sufficiently major food that the census itemizes it amongst subsistence products, and over half of rural households report harvesting these nuts. Importantly for the impact that forest destruction may have on inequality, Ngali is more important for the rural poor; 60 percent of the poorest quartile of rural households harvest and consume Ngali nut compared with just over 40 percent for the richest rural households (Jansen *et al.* 2006). To the extent that *Canarium* trees are destroyed, even if inadvertently, by logging, it will induce an inequality-increasing shock to environmental income. Similar effects are likely for water, since logging spoils streams and about one-fifth of households in the Solomon Islands drink from streams, while it tends to be only richer rural households that have an iron roof and water tank.

3. Data and Methods

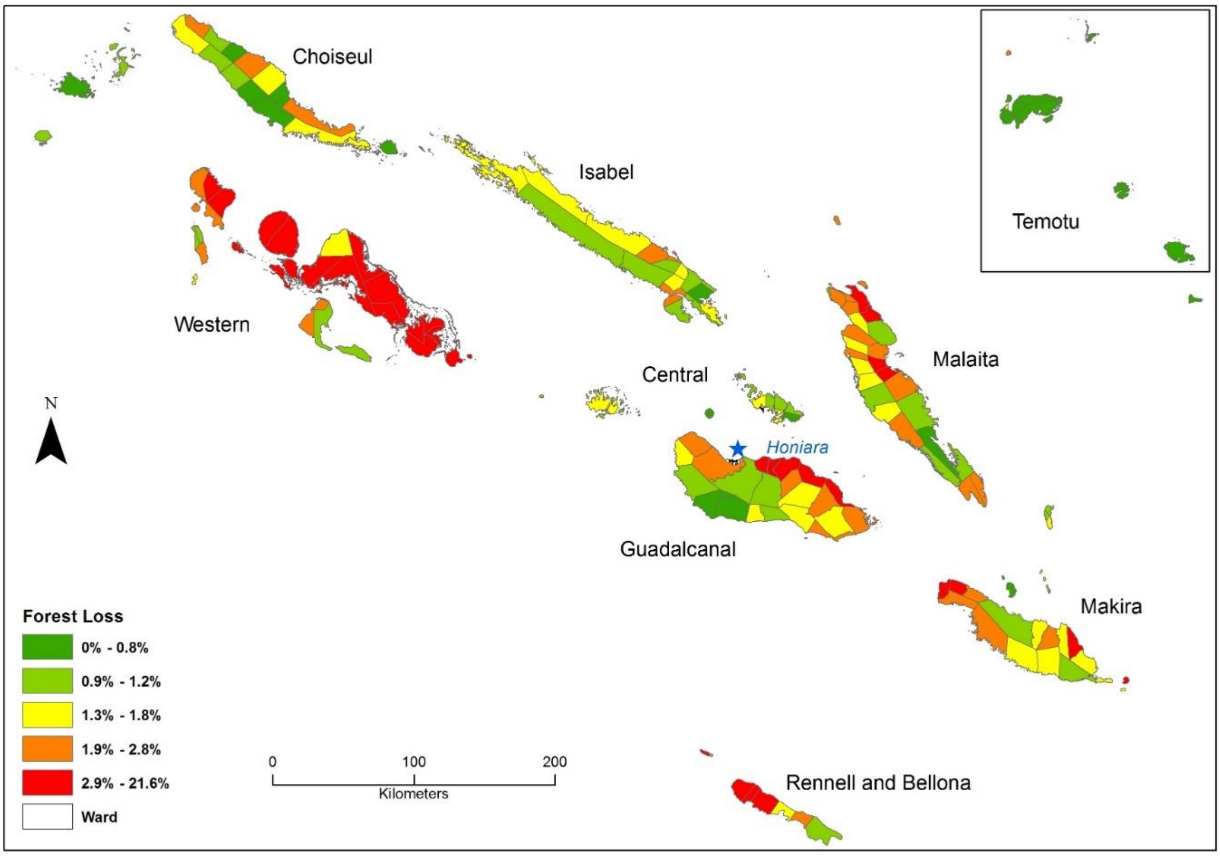
In order to study the relationship between forest loss and subsequent inequality, two types of databases are needed. The first is based on remote sensing data, from a well-known data source in environmental economics. The second uses less familiar methods, and is needed in order to derive welfare data – specifically inequality estimates – for small geographic areas that match the spatial scale of the remote sensing derived measures of forest loss.

3.1 Measuring Forest Change

The data on forests are from Hansen *et al.* (2013), and are based on Landsat 7 Enhanced Thematic Mapper Plus (ETM+) scenes from the growing season for each year from 2000 to 2012, at a spatial resolution of one arc-second (about 30 meters at the equator). In the Hansen et al data, forest loss is defined as either the complete removal of cover canopy for vegetation taller than 5 meters (which is rare in the Solomon Islands) or stand-replacing disturbance, after which the canopy composition likely will have more shade-intolerant trees that provide fewer ecological benefits (this is the main form of forest change in the Solomon Islands). These data indicate that 2.2% of forest was lost in the Solomon Islands from 2000 to 2012. There is a skew in the distribution; the median rural ward lost only 1.5% of their forest cover whereas up to one-fifth of forest cover was lost in the most badly affected wards.

The areas of greatest forest loss are concentrated on Western Province, although some smaller islands of that province had much lower loss rates (Figure 2). There are also high rates of forest loss in areas of Guadalcanal, to the east of the capital city, Honiara. Several of the main islands show a diversity of loss rates, which serves as a caution against carrying out a more aggregated analysis (say, at the provincial level) that may tend to average over some dissimilar experiences and possibly disguise any causal relationships.

Figure 2: Locations of Forest Loss from 2000 to 2012
Based on Hansen *et al.* (2013)



Notes: Temotu is shown at correct scale but moved ca. 450 km to fit into the map frame and allow a larger overall map scale. Names on the map are for provinces, and the location of the capital city is also shown.

3.2 Survey-to-Census Imputation for Measuring Small-Area Inequality

The inequality data are derived from the 2012/13 Solomon Islands Household Income and Expenditure Survey (HIES) whose sample of 4500 households was almost five percent of all households in the country. The survey ran from October 2012 to November 2013 so it is referred to here as measuring welfare in 2013. Even with this sample coverage the inequality estimates for real per capita consumption were only reported at the provincial level, with the Gini index varying from 0.25 to 0.39 across the nine provinces. In terms of precision, standard errors ranged from 5.2% to 11.1% of the value of the Gini index, with a mean relative standard error of 7.5%.

The HIES is not designed to be representative of wards, and only 144 of 168 rural wards are in the HIES sample. The number of surveyed households per ward ranged from 7 to 72, with a mean of 22, so it is impossible to directly use the survey to get ward-level results. By way of illustration, even restricting attention to wards with more than 30 surveyed households, in the hope that this might be enough sample for calculating representative inequality statistics, the standard errors of these ward-level Gini coefficients would range from 9.2% to 23.1% of the value of the index, with a mean relative standard error of 14.4%. Thus, if one relied solely on survey data, the inequality statistics would be available for only a fraction of the wards, would not be representative at the ward level, and would be fairly imprecise.

Instead, the small-area estimation approach of Elbers, Lanjouw and Lanjouw (2003) [ELL, hereafter] is used.[7] To start, a model of (log) per capita consumption for people living in household *h* in location *c* is estimated, where *c* is an enumeration area (or 'cluster'):

$$\ln\, y_{ch} = \mathbf{x}_{ch}'\boldsymbol{\beta} + u_{ch} \tag{1}$$

The vector of explanatory variables, $\mathbf{x}_{ch}$ is restricted to survey variables also in the census with distributions that overlap in each source. The parameter vector $\boldsymbol{\beta}$ has no causal interpretation; the equation is for prediction. The error u_{ch} is assumed to have two independent components: a cluster specific effect η_c and a household specific effect ε_{ch}.

The cluster specific effect reflects aspects of the environment common to households in the same location. If one just used survey data, these unseen elements could be controlled with cluster fixed effects. However, the survey sampled only 375 of the 1340 enumeration areas in the Solomon Islands so fixed effects give no way to deal with the other *n*=965 clusters. If location effects are ignored they end up in the residuals of equation (1), where they are potentially disruptive, in the sense that they make predictions less precise.[8] A common strategy, followed here, is to use the cluster means of household-level variables from the census data, which are available for all clusters. The residuals from equation (1) are then decomposed into the uncorrelated household idiosyncratic component and the correlated location component:

$$\hat{u}_{ch} = \hat{\eta}_c + \hat{\varepsilon}_{ch} \tag{2}$$

The $\hat{\eta}_c$ are within-cluster means of the overall residuals. The household components $\hat{\varepsilon}_{ch}$ are the overall household-level residuals net of the location components.

[7] This method is used to target billions of dollars of anti-poverty funds. Bedi *et al.* (2007) provide several examples, and a validation of the method using census data from Brazil is provided in Elbers *et al.* (2008). Details on the imputation software are in Zhao and Lanjouw (2003).

[8] If a large component of the error is common to groups of households rather than being idiosyncratic and random, the gains in precision that normally come from averaging over larger numbers are muted.

Heteroskedasticity in the household idiosyncratic component is estimated from:

$$\ln\left[\frac{\varepsilon_{ch}^2}{A-\varepsilon_{ch}^2}\right]=\mathbf{x}_{ch}^{'}\hat{\alpha}+r_{ch} \tag{3}$$

where $\mathbf{x}_{ch}$ are from variables in equation (1) and interactions between them and the predictions from equation (1), and A is set equal to $1.05\times\max\{\varepsilon_{ch}^2\}$. Equation (3) gives a household specific variance estimator for ε_{ch} which is inserted along the diagonal of an $n\times n$ square matrix, for each of the n surveyed households. A block matrix of the same size, where each block has the cluster variance along the diagonal, is added to form the variance-covariance matrix for the model, so that equation (1) can be re-estimated by Generalized Least Squares.

In the simulation stage, the estimated regression coefficients from equation (1) are applied to $\mathbf{x}_{ch}$ from the census to predict consumption for every census household. For each of r simulations a set of beta and alpha coefficients, $\tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\alpha}}$ are drawn from multivariate normal distributions based on the first stage point estimates and variance-covariance matrices. Additionally, $(\tilde{\sigma}_{\eta}^2)^r$ a simulated value of the variance of the location error component is drawn, and then equation (3) is applied to each census household to calculate the household-specific error component, $(\tilde{\sigma}_{\varepsilon,ch}^2)^r$ of the variance. Simulated disturbance terms, $\tilde{\eta}_c^r$ and $\tilde{\varepsilon}_{ch}^r$ are then drawn from their corresponding distributions. The consumption of each census household, $\hat{y}_{ch}^r$ is from the combined effect of the predicted log expenditure, $\mathbf{x}_{ch;}^{'}\tilde{\boldsymbol{\beta}}^r$ and the disturbance terms:

$$\hat{y}_{ch}^r=\exp\left(\mathbf{x}_{ch}^{'}\tilde{\boldsymbol{\beta}}^r+\tilde{\eta}_c^r+\tilde{\varepsilon}_{ch}^r\right) \tag{4}$$

The simulations are repeated 100 times, drawing a new set of coefficients and disturbance terms for each simulation. The full set of simulated $\hat{y}_{ch}^r$ values are used to measure inequality; the mean of the 100 simulations gives the point estimate of the Gini index for each small area, and the standard deviation serves as the estimated standard error.

The details on the models (equations (1) and (3)) used to generate the parameters for the simulations are in Appendix A. The consumption model for n=3,117 rural households from the HIES used 43 predictor variables, with an adjusted R^2=0.46. Just over half of the covariates were cluster means of household variables from the census, which helped reduce the share of total error variance due to the location component to below one-fifth. The heteroscedasticity model (equation (3)) used 11 predictor variables. The parameters from these models and their errors were used to impute consumption for n=75,716 census households.

A comparison of the inequality statistics calculated directly from the survey with those derived from the ELL survey-to-census imputation is reported in Table 1. At the provincial level, the standard errors on the survey-based Gini averaged 7.5% of the Gini index value. The imputed, census-based inequality statistics standard errors average just 4.1% of the index value (the indexes had similar averages, of 0.32 for the survey and 0.33 for the census).

Table 1: Comparison of Inequality Data

	Survey-based	ELL Survey-to-Census Imputed
Provincial Level – Rural Sector (*n*=9)		
Mean Gini index	0.32	0.33
Mean relative standard error (range)	7.5% (5.2% to 11.1%)	4.1% (3.0% to 6.3%)
Ward Level – Rural Areas Only (*n*=168)		
Mean Gini index	Not available	0.30
Mean relative standard error (range)		7.1% (3.8% to 20.0%)

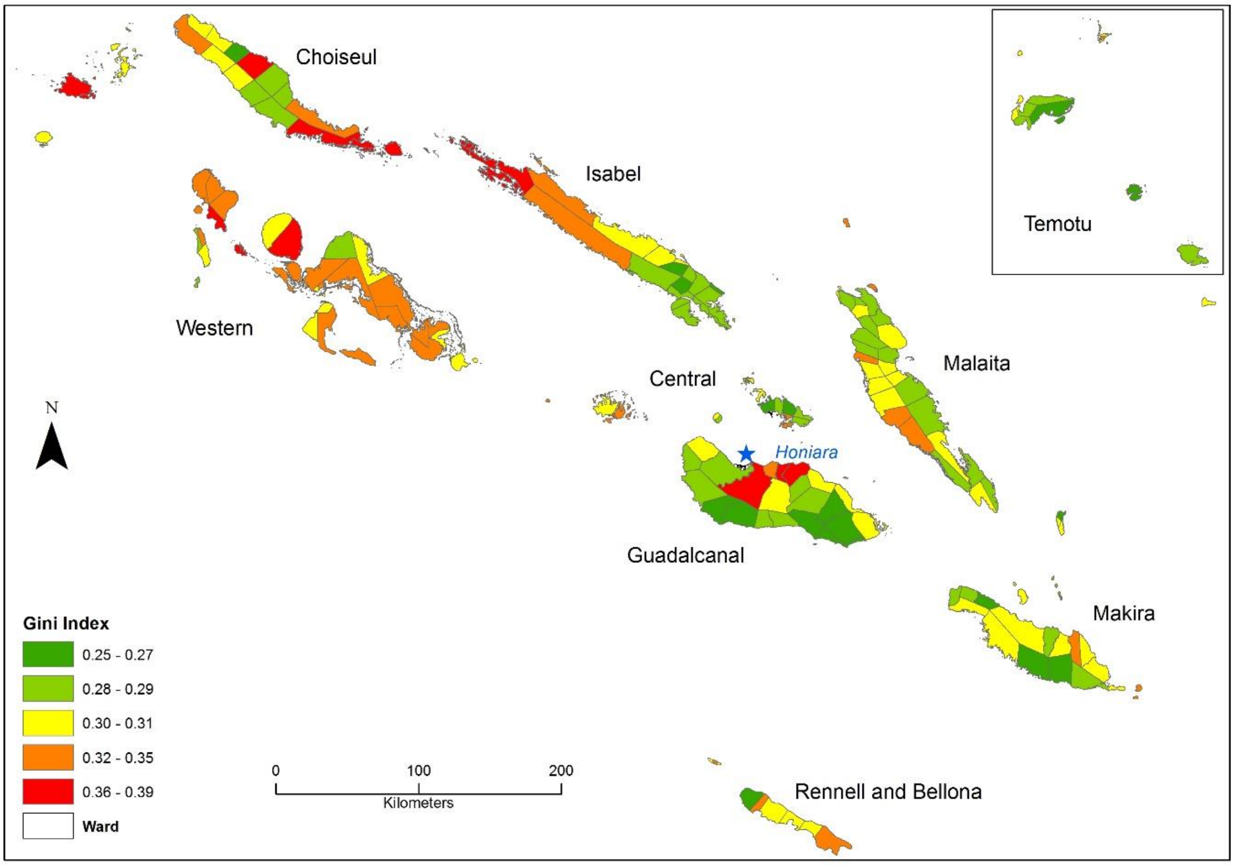
Notes: ELL stands for Elbers, Lanjouw and Lanjouw (2003). The relative standard error is the standard error as a percentage of the Gini index for each spatial unit.

The real benefit of using the census-based measures shows in the ward-level statistics, which are not reported by the survey and even if they were calculated from the household level data they would be unrepresentative at ward-level and imprecise. In contrast, the census-based measures cover every ward, since all households are included, and the estimates are far more precise than the survey-based ones, with standard errors that average 7.1% of the Gini index. Roughly speaking, the ELL method gives a level of precision equivalent to what the survey has at the next higher level of spatial aggregation (that is, at province rather than ward level).

In terms of spatial patterns, rural inequality appears to be higher in the west of the country, particularly in parts of Western, Choiseul and Isabel provinces (Figure 3). Inequality is lowest in the far eastern province of Temotu.[9] The ward-level Gini index for real per capita consumption of rural households ranges from 0.25 to 0.39 with a mean and median of 0.30. There is also considerable variation within some of the provinces, particularly Choiseul and Guadalcanal, where the within-province coefficient of variation of the ward-level Gini index is about 0.12. The heterogeneity in ward-level inequality suggests that information may be lost in analyses carried out at more aggregated levels such as provinces.

[9] These regions where inequality is lower tend to have a higher incidence of rural poverty, with a correlation between the Gini index and the headcount poverty rate of -0.31.

Figure 3: Spatial Patterns of Inequality, Based on ELL Small Area Estimation



Note: See Figure 2.

4. Results

The results of ordinary least squares (OLS) regressions of the ward-level Gini index, for rural per capita household consumption in 2013, on the percentage of the ward's forest that was lost over 2000 to 2012 are reported in Table 2. In addition to the results for a simple regression, there are four regressions that each add a single covariate, which are reported in columns (2) to (5). A regression with all covariates considered together is in column (6).

The regressions suggest that the higher the percentage of forest loss for a ward, the higher the subsequent economic inequality amongst rural households. The effect is precisely estimated, with statistical significance at the $p<0.01$ level for five regressions and $p<0.05$ for the other.[10] According to the results in column (1), if ten percent of the forest in a ward was lost (noting that this may be stand-replacing disturbance rather than clear-felling), the Gini index in 2013 would be 3.9 points higher. In unit-free terms, a standard deviation increase in forest loss increases inequality by one-third of a standard deviation (shown in [ ] in Table 2).

[10] In contrast, estimating at the provincial level using inequality estimates from the survey data gives a standard error 70% larger than the coefficient (t=0.58), and a coefficient twice as large as in Table 2.

Table 2: OLS Estimates of Effects of 2000-2012 Forest Loss on Gini Index for Per Capita Consumption Inequality in 2013 for Rural Wards of the Solomon Islands

	(1)	(2)	(3)	(4)	(5)	(6)
Percent of forest lost 2000-2012	0.394	0.392	0.377	0.278	0.389	0.224
	(3.56)**	(3.56)**	(3.45)**	(2.71)**	(3.51)**	(2.18)*
	[0.34]	[0.34]	[0.32]	[0.24]	[0.33]	[0.19]
Headcount poverty rate		-0.069				0.009
		(5.43)**				(0.44)
ln population			0.003			0.006
			(1.17)			(2.95)**
ln per capita consumption				0.052		0.058
				(5.84)**		(4.47)**
ln baseline forested area					0.001	0.000
					(0.54)	(0.09)
Constant	0.292	0.303	0.272	-0.182	0.284	-0.288
	(97.34)**	(79.00)**	(15.47)**	(2.26)*	(21.20)**	(2.33)*
R-squared	0.114	0.207	0.120	0.377	0.115	0.409

Notes: *N*=168 rural wards, robust t statistics in parentheses, **, * denote significance at the 1%, 5% level. Beta coefficients for the effects of a std deviation change in % forest loss on std deviation of the Gini in [ ]

The effect of forest loss on inequality is robust to the inclusion of either the ward-level headcount poverty rate, the ward population, or the baseline forest cover. The only covariate that reduces the effect of forest loss on inequality is the average log per capita consumption in the ward (based on the census-derived estimates). The regression coefficient on forest loss drops from 0.39 to 0.28, and the standardized coefficient drops from 0.34 to 0.24 once average per capita consumption is controlled for. Thus about one-quarter of the effect of forest loss on inequality that is seen in column (1) for the model with no other covariates reflects the indirect pathway of the effect of forest loss on average income levels (the correlation is 0.19), and the effect of higher incomes on inequality (the correlation is 0.57).

It should be noted that although inequality is the welfare indicator considered here, the effect of forest loss on poverty can also be seen, indirectly, from the results in Table 2. The poverty rate can be decomposed into mean income (as proxied by consumption) and inequality components (Datt and Ravallion 1992). Thus, the significant effect of forest loss on inequality when mean income is held constant (as in columns (4) or (6) of Table 2), implies that poverty will be higher (since higher inequality with constant mean income gives higher poverty). In particular, if the dependent variable in column (4) was changed from the Gini index to the headcount poverty rate (poverty gap index) the standardized coefficients would be 0.12 (0.13) and these are statistically significant at the $p<0.02$ level.[11] In other words, deforestation seems to increase inequality not only by raising average incomes

[11] The poverty gap index gives the mean distance below the poverty line, expressed as a proportion of that line, where the mean is formed over the entire population (counting the non-poor as having zero poverty gap).

through a process where some people get richer than others but also by increasing poverty. Both of these effects are consistent with the pathways noted above, where the poor rely more on environmental income, and so forest loss may harm their livelihoods, and where the payments made by logging companies may not spread widely and instead benefit only a subset of tribal members.

The regression results in Table 2 rely on an imputed measure as the dependent variable; specifically the ward-level mean of the 100 Gini index estimates from replications of the ELL procedure (based on equation (4)). These replications also provide a standard deviation, so it is possible to put more weight on those wards where inequality is more precisely estimated. The weighted least squares (WLS) results reported in Table 3 have a slight gain in the statistical significance of the estimated effects of forest loss, and almost no change in coefficient magnitudes compared to Table 2.

Table 3: Weighted Least Squares Estimates of Effects of 2000-2012 Forest Loss on Gini Index for Per Capita Consumption Inequality in 2013 for Rural Wards of the Solomon Islands

	(1)	(2)	(3)	(4)	(5)	(6)
Percent of forest lost 2000-2012	0.404	0.395	0.393	0.261	0.404	0.206
	(3.92)**	(3.97)**	(3.85)**	(2.85)**	(3.86)**	(2.23)*
	[0.35]	[0.34]	[0.34]	[0.23]	[0.35]	[0.18]
Headcount poverty rate		-0.060				0.010
		(5.69)**				(0.56)
ln population			0.002			0.005
			(0.67)			(2.43)*
ln per capita consumption				0.054		0.060
				(6.57)**		(4.89)**
ln baseline forested area					0.000	-0.000
					(0.05)	(0.26)
Constant	0.288	0.298	0.276	-0.203	0.287	-0.298
	(109.60)**	(90.37)**	(16.25)**	(2.73)**	(23.00)**	(2.54)*
R-squared	0.122	0.211	0.124	0.381	0.122	0.402

Notes: Observations are weighted by the standard error of the Gini index from the ELL simulations, to put more weight on the Wards with the most precise estimates. Other notes, see Table 2.

The results reported thus far do not allow for spatial autocorrelation, where regression errors for one observation are correlated with errors in neighboring observations, which violates the independence assumption of OLS. These spatial features of the data are often neglected in studies of the relationship between inequality and environmental quality; a review of almost 100 studies by Cushing *et al.* (2015) found just one study that considered these. In fact, in the data for the Solomon Islands there is a modest, but statistically significant degree of spatial autocorrelation in the data for both forest loss and baseline forest area, as shown by Moran's *I* statistics of 0.07 (p<0.07) and 0.10 (p<0.03).[12] Whether this will matter to the regression modelling is unclear because there is no evidence of spatial autocorrelation in either inequality or log per capita consumption, so the patterns for the observed variables do not give a clear guidance on the likely patterns in the unobserved errors.

Table 4: Spatial Error Model of the Effects of 2000-2012 Forest Loss on Gini Index for Per Capita Consumption Inequality in 2013 for Rural Wards of the Solomon Islands

	(1)	(2)	(3)	(4)	(5)	(6)
Percent of forest lost 2000-2012	0.351 (3.99)**	0.361 (4.38)**	0.291 (3.26)**	0.268 (3.66)**	0.328 (3.72)**	0.192 (2.57)*
Headcount poverty rate		-0.068 (4.06)**				0.013 (0.65)
ln population			0.005 (1.53)			0.008 (2.97)**
ln per capita consumption				0.052 (8.29)**		-0.000 (0.04)
ln baseline forested area					0.001 (0.52)	0.058 (7.05)**
Constant	0.293 (96.05)**	0.304 (79.27)**	0.261 (11.73)**	-0.181 (3.17)**	0.285 (16.25)**	-0.295 (3.64)**
Spatial error (rho)	0.195 (1.98)*	0.119 (1.18)	0.269 (2.66)**	0.050 (0.50)	0.207 (2.11)*	0.153 (1.44)

Note: Estimated by generalized spatial two-stage least squares, using the spreg package of Drukker *et al.*(2013). Other notes, see Table 2.

In order to rule out any concern that inferences are affected by spatial autocorrelation, Table 4 reports the results of a spatial error model. In this model, the regression error for each ward is allowed to be influenced by a weighted average of the errors in the adjacent wards, where the spatial weights matrix is based on contiguity (for ward i, any ward j whose boundary touches the boundary of ward i is a neighbor, and otherwise it is not). The table has an extra row, compared with the earlier regression tables, for the estimate of ρ, the coefficient on the spatial error term. In some specifications of the spatial error model there is evidence that the errors for the i^{th} ward are correlated with the errors in adjacent wards, with estimates of ρ around 0.2 but this effect disappears in any specifications that include either the headcount poverty rate or the ward average of log per capita consumption. Moreover, with the exception of column (3), there are more precise estimates of the effect of forest loss on inequality in Table 4 than in Table 2, so unaccounted for spatial autocorrelation should not have biased inferences made from the results reported above. In terms of the magnitude of the

[12] For any variable z in deviation from mean form and spatial weights matrix W, Moran's I is equivalent to the slope coefficient in a linear regression of Wz on z (Anselin 1988). In other words, it examines the strength of the relationship between one observation and the spatially weighted average of its neighboring observations.

effect, the coefficients in Table 4 are about 90% of the size of those in Table 2, so estimated effects of forest loss on subsequent inequality can be considered robust to the treatment for spatial autocorrelation.[13]

4.1 Controlling for Baseline Welfare

The last threat to validity considered is the possibility of reverse causation, where the true relationship is from inequality to forest loss rather than the reverse. The identifying assumption being made is that the sharp increase in total log exports and the change in export destinations since 2001 reflects developments outside of the Solomon Islands, and is thus an exogenous shock. Therefore, even if previous logging depended on local inequality, as might be argued by extrapolating from cross-country studies such as Koop and Tole (2001), those determinants of previous logging are less relevant to the change in logging since 2001.

Notwithstanding this identifying assumption, it would help to have baseline data on ward-level inequality prior to 2001. Specifically, controlling for prior inequality would allow an interpretation akin to a difference-in-difference specification. There was only one national household survey in that era - the 1993 Household Income and Expenditure Survey - and all of the questionnaires and data tapes were lost when part of the statistics office was destroyed during ethnic tensions in Honiara in the early 2000s. While copies of the summary report from that survey survive, they only have provincial level estimates of welfare variables.[14]

However, a proxy for baseline welfare, that may also proxy for inequality since richer areas are more unequal, is available in the form of a wealth index used by Jansen et al (2006). This index used the 1995 Village Resources Survey, which provided ward-level data on public facilities such as schools, clinics, and aid posts, along with data on a number of private facilities that may correlate with economic activity and wealth, including the number of markets, trade stores, and various other businesses. The wealth index was constructed following the approach of Filmer and Pritchett (2001), who show that principal components can be used to provide the weights for combining indicators into a single ranking variable if the more typical expenditure data used to measure welfare are unavailable. The rural wards from 1995 were also divided into wealth quartiles on the basis of this index by Jansen *et al.* (2006). These wards match the boundaries shown in the maps in Figures 2 and 3.

If the wealth index is added to regressions that are otherwise the same as in Table 2, there is almost no change in the estimated effect of forest loss on inequality. The coefficients range from 96% to 101% of their corresponding value in Table 2, and the level of statistical

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[13] A more general spatial autoregressive model was also considered, that included the spatial lag of the Gini index (the weighted average of the Gini index for adjacent wards). The spatial lag terms were generally insignificant, while the coefficients on the spatial error terms were similar to those in Table 4 and the coefficients on forest loss were about 13% higher than those in Table 4.

[14] *Statistical Bulletin No. 18/95* 'Rural Areas of Solomon Islands Income and Expenditure Survey 1993' Statistics Office, Honiara, September 1995.

significance is unchanged. The coefficients on the wealth index are statistically insignificant in these regressions (the most precisely estimated (t=1.87) is when ward population is a covariate) and this suggests that prior indicators of ward-level wealth do not predict current inequality. This is consistent with the identifying assumption that the dramatic expansion of logging since 2001 has acted as an exogenous shock to rural incomes and welfare. Likewise, if the wealth quartile is included in the regressions the coefficients (t statistics) on the forest loss variable are from 96% to 101% (100% to 112%) of their corresponding value in Table 2 (while the t statistics on the wealth quartile variable average 1.4). Thus, to the extent possible with the limited data, the reverse pathway from existing inequality to higher deforestation can be ruled out, and the results in Tables 2 to 4 can be interpreted as identifying the effect of forest loss on subsequent inequality.

5. Conclusions

It is important for a country such as the Solomon Islands to have clear evidence on the costs and benefits of deforestation. The economic benefits are very clear to policy makers since about one-half of foreign exchange and one-sixth of government revenue are from logging. However, the evidence on costs is mostly in terms of environmental damage, due to poorly monitored 'selective' logging (for example, Katovai *et al*. 2015) and it is possible that policy makers discount this evidence since the Solomon Islands remains heavily forested. In this paper, new evidence is reported on one immediate welfare cost of deforestation, which is that there is higher local economic inequality within the affected areas. Specifically, if ten percent of the forest cover in a ward was lost over the 2000 to 2012 period, the Gini index in 2013 would be 3.9 points higher. In many settings, policy makers reveal an aversion to increased inequality, so knowing that a standard deviation rise in the rate of forest loss raises local inequality by one-third of a standard deviation in the rural Solomon Islands may help local policy makers to better focus on some of these welfare costs of logging.

In terms of methodology, these estimates of how deforestation affects local inequality would not be possible without the survey-to-census imputation approach to getting small-area estimates of welfare statistics. This technique is rarely used in environmental economics, yet it lets one link remote sensing data on environmental change to data on human welfare indicators at a spatial scale that better matches the scale of decision-making units. In the Solomon Islands, where most forests are under customary ownership, the spatial structure of the units used here (wards) is due to the same topographic factors that affect tribal boundaries and that also affect the patterns of deforestation. Consequently, there is less risk of ecological fallacy in research carried out with these spatially detailed data. In contrast, if one only had the survey data to rely on, which would necessitate carrying out analyses at provincial level, the effect of deforestation on subsequent inequality would be obscured.

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Appendix A1: Estimates of Equation (1) for Predicting Consumption

Variable Name	Coefficient	Std. Err.	t-stat	|Prob|>t	Variable Label
intercept	10.8691	0.2746	39.5772	0	Intercept
COOK_WOOD_1	-0.3383	0.0648	-5.2204	0	Dummy for COOK_WOOD=1
DWELL_NROOMS	0.0632	0.0101	6.2746	0	dwell_nrooms
DWELL_TINROOF_1	0.1686	0.0258	6.53	0	Dummy for DWELL_TINROOF=1
EMPL_INACTIVE	-0.3767	0.0646	-5.8304	0	empl_inactive
EMPL_SELF	-0.3176	0.0547	-5.8096	0	empl_self
F06	0.3213	0.0899	3.5746	0.0004	f06
F1550	0.1895	0.0748	2.5315	0.0114	f1550
HAS_MOTORBOAT_1	0.1908	0.0376	5.0719	0	Dummy for HAS_MOTORBOAT=1
HEAD_NONMELANESIAN_1	0.2209	0.0487	4.5371	0	Dummy for HEAD_NONMELANESIAN=1
HEAD_SUBGR6_1	-0.059	0.0244	-2.4151	0.0158	Dummy for HEAD_SUBGR6=1
HHSIZE	-0.2143	0.0158	-13.5729	0	hhsize
HHSIZE2	0.0077	0.0011	6.9581	0	hhsize2
M06	0.3958	0.0828	4.7802	0	m06
M1550	0.2541	0.0694	3.6601	0.0003	m1550
MEAN_COOK_GAS	-1.7551	0.47	-3.734	0.0002	mean_cook_gas
MEAN_DWELL_NROOMS	0.0524	0.0236	2.2169	0.0267	mean_dwell_nrooms
MEAN_DWELL_TEMPWALL	-1.4063	0.4514	-3.1152	0.0019	mean_dwell_tempwall
MEAN_DWELL_TINROOF	0.2238	0.0767	2.9165	0.0036	mean_dwell_tinroof
MEAN_EACHURCH	-0.2324	0.0444	-5.2395	0	mean_EAchurch
MEAN_EMPL_EMPLOYER	-11.0474	3.9851	-2.7722	0.0056	mean_empl_employer
MEAN_EMPL_INACTIVE	0.5474	0.2336	2.343	0.0192	mean_empl_inactive
MEAN_EMPL_SELF	0.9498	0.2995	3.171	0.0015	mean_empl_self
MEAN_F714	-1.0418	0.5681	-1.8338	0.0668	mean_f714
MEAN_HAS_CARBUSTRUCK	3.5055	0.5906	5.9356	0	mean_has_carbustruck
MEAN_HAS_FRIDGE	-1.0946	0.5022	-2.1798	0.0293	mean_has_fridge
MEAN_HAS_MOTORBOAT	1.3366	0.1895	7.0542	0	mean_has_motorboat
MEAN_HEAD_AGE	-0.0099	0.0042	-2.3613	0.0183	mean_head_age
MEAN_HEAD_EMPLOYER	6.008	1.8589	3.232	0.0012	mean_head_employer
MEAN_HEAD_SELF	-0.6047	0.1579	-3.8304	0.0001	mean_head_self
MEAN_HEAD_SUBGR6	-0.1298	0.0791	-1.6401	0.1011	mean_head_subgr6
MEAN_HHSIZE	0.0603	0.0201	3.0023	0.0027	mean_hhsize
MEAN_M06	-2.0849	0.5939	-3.5103	0.0005	mean_m06
MEAN_M714	-2.96	0.5903	-5.0141	0	mean_m714
MEAN_TENURE_FREE	-0.2986	0.0446	-6.6883	0	mean_tenure_free
MEAN_TENURE_RENT	-4.0058	0.7607	-5.2656	0	mean_tenure_rent
MEAN_TOILET_OWNPIT	-0.1057	0.0529	-1.9965	0.046	mean_toilet_ownpit
MEAN_WATER_HHTANK	-0.5689	0.0912	-6.2402	0	mean_water_hhtank
MEAN_WATER_RIVER	-0.193	0.0521	-3.7025	0.0002	mean_water_river
MEAN_WATER_STANDPIPE	-0.2982	0.046	-6.4899	0	mean_water_standpipe
TOILET_OWNFLUSH_1	0.2603	0.0631	4.128	0	Dummy for TOILET_OWNFLUSH=1
WASH_RIVER_LAKE_SEA_1	-0.0438	0.0232	-1.8856	0.0594	Dummy for WASH_RIVER_LAKE_SEA=1
WATER_HHTANK_1	0.1204	0.0333	3.6143	0.0003	Dummy for WATER_HHTANK=1

Appendix A2: Estimates for Equation (3) for Modelling Heteroscedasticity

Variable Name	Coefficient	Std. Err.	t-stat	|Prob|>t	Variable Label
intercept	-2.7536	0.3597	-7.6546	0	Intercept
COOK_WOOD_1*_yhat_*_yhat_	-0.0166	0.0039	-4.2163	0	Dummy for (COOK_WOOD)=1*_yhat_*_yhat_
M1550*_yhat_	-1.915	0.4648	-4.1203	0	m1550*_yhat_
M1550*_yhat_*_yhat_	0.2064	0.0488	4.2333	0	m1550*_yhat_*_yhat_
MEAN_HAS_CARBUSTRUCK	-6.683	2.8308	-2.3608	0.0183	mean_has_carbustruck
MEAN_TENURE_FREE	-126.8487	52.7272	-2.4058	0.0162	mean_tenure_free
MEAN_TENURE_FREE*_yhat_	28.9619	11.6658	2.4826	0.0131	mean_tenure_free*_yhat_
MEAN_TENURE_FREE*_yhat_*_yhat_	-1.643	0.6444	-2.5499	0.0108	mean_tenure_free*_yhat_*_yhat_
MEAN_TENURE_RENT*_yhat_*_yhat_	-0.1028	0.0532	-1.9318	0.0535	mean_tenure_rent*_yhat_*_yhat_
MEAN_WATER_RIVER	-0.6255	0.2052	-3.048	0.0023	mean_water_river
MEAN_WATER_STANDPIPE	-0.6169	0.1728	-3.5701	0.0004	mean_water_standpipe