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Valuing Water Purification Services of Forests

A Production Function Approach using Panel Data from China's Sichuan Province

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Valuing Water Purification Services of Forests: A Production Function Approach using Panel Data from China's Sichuan Province

Zhaoyang Liu*

Abstract

The water purification functions of forests represent one of the most frequently invoked examples of nonmarket ecosystem services that are economically valuable. Yet, there has been a paucity of statistical estimates that robustly quantify such benefits. This study enriches this thin evidence base through valuing forests' water purification services in the form of the ensuing cost savings of municipal drinking water treatment, using a rich panel dataset from China's Sichuan province. The panel nature of the dataset has enabled the estimation of fixed effects models, which control for a wide range of observed and unobserved factors that might otherwise have biased the estimates of interest. Moreover, this study has undertaken a novel spatial piecewise approach to investigate the spatial patterns of such cost savings delivered by forests at different distances from the water intake point. The estimation results find statistically significant evidence that substantiates the expected cost saving effect of forests only within a 3km radius upstream from the water intake point. This transferrable methodological twist helps facilitate the optimal spatial targeting of forest conservation.

Keywords: ecosystem service; water purification; forest; valuation; drinking water treatment; production function; spatial piecewise approach; fixed effects panel data model

JEL Codes: Q24; Q25; Q51; Q57

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1. Introduction

The water purification functions of forests represent one of the most frequently invoked examples of nonmarket ecosystem services that are economically valuable (Freeman, Herriges, & Kling, 2014; Vincent et al., 2016). Forests (and other natural ecosystems such as wetlands) help enhance water quality by reducing soil erosion (and hence reducing silt) as well as filtering out nutrients and pollutants carried in water, which allows the municipal water supply sector to simplify or expedite many costly water treatment procedures and thereby save on operating costs (Millennium Ecosystem Assessment, 2005). Despite that, there has been a paucity of statistical estimates that robustly quantify such cost savings (Ferraro, Lawlor, Mullan, & Pattanayak, 2012; Price & Heberling, 2018), which has precluded inclusion of this essential ecosystem service in large-scale programmes intended to mainstream ecosystem services into national accounts, such as the UK National Ecosystem Assessment (Bateman et al., 2013). There has been a recent and limited body of literature that attempts to bridge this gap, such as the studies of Abildtrup et al. (2013), Lopes et al. (2019), Singh and Mishra (2014), Vincent et al. (2016), and Westling et al. (2020). Among these studies, only Vincent et al. (2016) and Westling et al. (2020) undertook fixed-effects panel data estimation, a quasi-experimental approach that seeks to better identify the water treatment cost savings 'caused' by forests, as opposed to those that are in fact induced by other unobserved 'confounding factors' but are likely to be mistakenly attributed to forests (Greenstone & Gayer, 2009; Imbens & Wooldridge, 2009).[1]

Moreover, the spatial patterns of such cost savings delivered by forests at different distances from the water intake point remain less understood. Existing studies typically focus on the average effect of forest cover in the entire catchment area [e.g. Singh and Mishra (2014), and Vincent et al. (2016)].[2] Such estimates suffice for the valuation and accounting of the average or aggregate value of water purification services of forests in each catchment area. However, the provision of such services (via forest conservation) nearly always entails costs to society such as administrative costs of conservation activities and forgone benefits of alternative land use (Armsworth, 2014; Pearce, 2004). Economically optimal land use decision making critically depends on whether the benefits of such services (savings of drinking water treatment costs) outweigh the costs of forest conservation. Yet, such benefits

[1] Lopes et al. (2019) performed instrumental variable estimation, another quasi-experimental approach. Yet this study instrumented another explanatory variable of drinking water treatment costs (the volume of treated water), instead of forest cover.
[2] Lopes et al. (2019) and Westling et al. (2020) measured the average effect of forest cover within a predetermined radius (10km and 100km respectively) of the water intake point, whereas Abildtrup et al. (2013) used forest cover in the entire administrative division served by a drinking water treatment works. Such practices are prone to considerable measurement error, because, intuitively, only forests within the upstream catchment area (as opposed to forests in other locations) have implications for water quality at the water intake point.

and costs tend to be spatially heterogenous (Polasky et al., 2008; Vincent et al., 2016). Therefore, the cost-effective provision of water purification services via forest conservation would necessitate a better understanding of the presumably location-specific implications of forest cover for drinking water treatment costs. For instance, intuition might suggest that upstream forest cover within a certain radius of the water intake point is likely to have a larger effect on water treatment costs, relative to forest cover in a farther upstream location, because solids and other pollutants entrained by surface runoff in farther upstream locations may have been naturally removed before they could reach the water intake point, due to sedimentation and other self-purification functions of water bodies. In that case, it might be worthwhile to undertake forest conservation actions within that radius of the water intake point, but the opposite might be true for more distant locations or the entire catchment area. This is particularly relevant if water treatment works extract water from large rivers with massive catchment areas.

This study seeks to contribute to this literature through a spatial piecewise analysis of the effects of forest cover on drinking water treatment costs. I undertook fixed effects estimation using a rich panel dataset that contains annual observations on the drinking water treatment works of 170 county-level administrative divisions of China's Sichuan province during 1992–2015. This allows me to control for many unobserved confounding factors that might bias the estimated water treatment cost savings attributable to forest cover. Further, I performed a Heckman correction and a placebo test to formally assess the implications of missing data and potential confounders for the estimates of interest. This study thus enriches the currently thin evidence base around the monetary value of water purification services of forests. Moreover, the spatial piecewise approach[3] enables me to identify the farthest upstream distance beyond which forest cover no longer directly affects water treatment costs. I first delineated a sequence of equal distance concentric circles or buffers (with a 1km step length) surrounding each water intake point. I next measured the forest cover within the overlapping areas between the catchment and each buffer, giving rise to a vector of variables that represent forest cover within different radiuses of the water intake point. These forest cover variables enter the regression model individually, which reveals the threshold radius where the effect of forest cover on water treatment costs just disappears.

Such spatially explicit quantification of forests' water purification services has pronounced implications for developing countries in the tropics that are subject to continuing net losses of natural forests (Song et al., 2018) and limited access to safe drinking water (United Nations Childrens Fund & World Health Organization, 2019). For instance, it was estimated that only 35% of the population in the world's least developed regions was covered by safely managed drinking water services in 2017 (United Nations Childrens Fund & World

[3] This was adapted from the study of Tibesigwa and Siikamäki et al. (2019), which concerns forests' benefits for cultivation activities in terms of providing habitats for natural pollinators.

Health Organization, 2019). In the upcoming decade, these regions will need heavy investments in sanitised drinking water supply in order to achieve the United Nations' Sustainable Development Goal 6: ensure safe drinking water for all by 2030. Preserving forests' water purification services may help rein in such costs, which might be particularly pertinent for developing regions under tight constraints on public spending. However, local households in these regions tend to rely heavily on forest extraction as an essential source of livelihoods (Wunder, Noack, & Angelsen, 2018). In these contexts, the within-catchment optimal targeting of forest conservation actions takes on particular importance in terms of reducing drinking water treatment costs on the one hand, and protecting local livelihoods on the other. This study, admittedly, did not collect data from the tropics and the results may not be globally generalisable. Despite that, this study demonstrates a viable empirical approach that facilitates the identification of the forests (within a catchment) that provide the most materialisable water purification services to local residents. This empirical approach constitutes the primary contribution of this study and is transferrable to other geographic contexts.

The remainder of this paper is structured as follows. Section 2 describes the study area, data sources and measurement of variables. Section 3 performs the econometric analysis and reports the results, which substantiate water purification services of forests within a 3km radius upstream of the water intake point. The final section discusses these findings and concludes.

2. Study Area, Data and Variables

The geographic focus of this study is China's Sichuan province (Figure 1). In 2018, the province had a population of over 80 million and its economy was similar in size to Switzerland in terms of GDP (National Bureau of Statistics of China, 2019). The province's forests are widely considered to have a pivotal role in the delivery of watershed services and biodiversity. Sichuan is one of the only two provinces of China that accommodate the upper courses of both the Yangtze River and Yellow River, the two largest rivers of the country. Its forests contribute greatly to water inflows to both rivers. Moreover, they provide vital habitats for a variety of endangered species, including the giant panda. Therefore, central and local government bodies have been heavily investing in forest conservation and restoration programmes, such as the Sloping Land Conversion Programme that retires highly erodible agricultural lands and converts them to woodlands. Public spending on forest conservation and restoration in Sichuan province in 2018 amounted to CNY 9.5bln (USD 1.4bln) (National Bureau of Statistics of China, 2019), which is a considerable sum, using the annual cost of the US Conservation Reserve Program (USD 1.8bln) as a reference point (Hellerstein, 2017). However, less is known about the economic returns of forest conservation and restoration, which adds to the difficulty of setting such activities at the optimal level (where the benefits outweigh the costs). The postulated water purification services of forests would represent a highly perceivable nonmarket benefit of forests that continuously accrues to society.

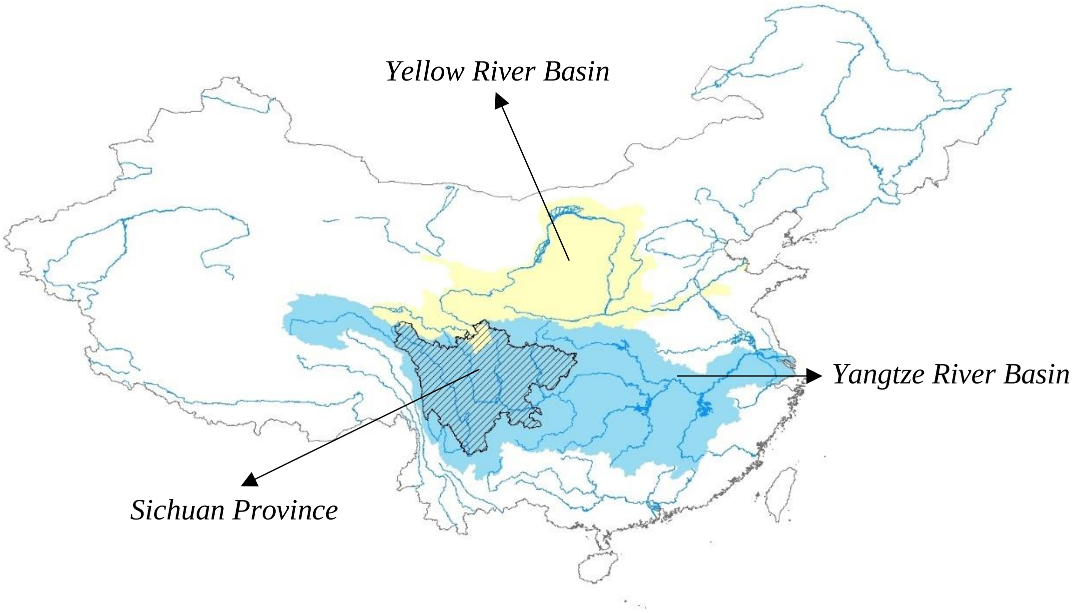


Figure 1: Location of Sichuan Province on a Watershed Map of China

Note: Source of the watershed map: The Chinese Academy of Sciences.

The water purification effect of forests is modelled as an input to the production of drinking water, following the theoretical framework of Freeman et al. (2014) and Vincent et al. (2011). The production function is assumed to take the Cobb-Douglas functional form: [4]

$$z = \boldsymbol{x}_1^{\alpha}\boldsymbol{x}_2^{\beta}\boldsymbol{e}^{\gamma}. \qquad \text{Eq.1}$$

In this production function, $\boldsymbol{x_1}$ represents a vector of variable inputs such as raw water, chemicals, labour and electricity; $\boldsymbol{x_2}$ denotes a vector of fixed inputs such as machinery; $\boldsymbol{e}$ consists of a vector of environmental factors that are exogenous to production decisions, such as forest cover and rainfall. Producers (water treatment works) choose the amounts of variable and fixed inputs that minimise the long-run production costs (since my dataset shows considerable adjustments in production assets during the 24 year period it covers), given exogenous levels of output $\tilde{z}$ and environmental factors $\tilde{\boldsymbol{e}}$. Solving this cost minimisation problem gives rise to the conditional factor demands:

$$\boldsymbol{x}_1^* = \left[\left(\frac{w_1\beta}{w_2\alpha}\right)^{-\beta}\tilde{\boldsymbol{e}}^{-\gamma}\tilde{z}\right]^{\frac{1}{\alpha+\beta}}, \qquad \text{Eq.2}$$

$$\boldsymbol{x}_2^* = \left[\left(\frac{w_2\alpha}{w_1\beta}\right)^{-\alpha}\tilde{\boldsymbol{e}}^{-\gamma}\tilde{z}\right]^{\frac{1}{\alpha+\beta}}, \qquad \text{Eq.3}$$

[4] As described in Appendix II, I tested an alternative production function involving both the quantity and quality of output, which was adapted from the model of Grieco and McDevitt (2017), and the findings are largely stable.

where w_1 and w_2 represent prices of x_1 ***and*** x_2. The unit production cost can thus be expressed as:

$$\bar{c} = \frac{c}{\tilde{z}} = \frac{w_1 x_1^* + w_2 x_2^*}{\tilde{z}} = K\boldsymbol{w}_1^{\frac{\alpha}{\alpha+\beta}} \boldsymbol{w}_2^{\frac{\beta}{\alpha+\beta}} \tilde{\boldsymbol{e}}^{-\frac{\gamma}{\alpha+\beta}} \tilde{z}^{\left(\frac{1}{\alpha+\beta}-1\right)}, \quad \text{Eq.4}$$

where $K = \left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}}$. Taking the logarithm of both sides yields the regression model to be estimated:

$$ln\bar{c} = lnK + \frac{\alpha}{\alpha+\beta} ln\boldsymbol{w}_1 + \frac{\beta}{\alpha+\beta} ln\boldsymbol{w}_2 - \frac{\gamma}{\alpha+\beta} ln\tilde{\boldsymbol{e}} + \left(\frac{1}{\alpha+\beta} - 1\right) ln\tilde{z}, \quad \text{Eq.5}$$

where the coefficient on $ln\tilde{\boldsymbol{e}}$ represents the elasticity of the unit drinking water treatment cost with respect to environmental factors, which captures the monetary value of forests' water purification services. This theoretical framework provides a basis for the selection of regressors in the empirical analysis.

A full catalogue of the geographic coordinates of 276 urban drinking water intake points in Sichuan province was obtained from the Ministry of Ecology and Environment of China. This has enabled the delineation of the upstream catchment area of each water intake point, within which the surface runoff drains into the water intake point (as illustrated in Figure 2). I next drew a sequence of equal distance concentric circles or buffers (with a 1km step length) surrounding each water intake point. I then measured the area and percentages of different land use types within the overlapping areas between the catchment and each buffer (the shaded areas in Figure 2). In contrast, forests in the remaining fractions of the buffers outside the catchment (the unshaded portions of the buffers in Figure 2) will be used as a placebo test, as will be detailed shortly. The land use dataset was sourced from the Climate Change Initiative of the European Space Agency (https://www.esa-landcover-cci.org/?q=node/175), which consists of consecutive annual land use data from 1992–2015 with a spatial resolution of 300m.[5] Moreover, following Singh and Mishra (2014) and Vincent et al. (2016), I controlled for rainfall in these buffers, which is likely to correlate with both land use changes and water quality (and hence drinking water treatment costs). The rainfall dataset was obtained from the Climate Research Unit of the University of East Anglia (Harris, Jones, Osborn, & Lister, 2014; Osborn & Jones, 2014), which contains monthly rainfall data for the same period (1992–2015). This dataset has an original spatial resolution of 0.5 degrees and was resampled to a 30m resolution. The land use and rainfall variables constitute the vector of environmental inputs ($\tilde{\boldsymbol{e}}$) in Eq. 5.

[5] The original land use dataset classifies 22 first-level land use types (ESA Climate Change Initiative, 2017). I selected a subset of these types and regrouped them into cropland (original first-level classification codes 10 and 20), forestland (original codes 50, 60, 70, 80, 90, 120), and urban areas (original codes 190, 200, 201, 202). Other land use types either only account for a trivial fraction of the buffers in my dataset, or represent a mosaic of diverse land use types (e.g. crops and natural vegetation) which may have mixed effects on water quality.

Annual water treatment data were extracted from *the Statistical Yearbook of City Water Supply* and *the Statistical Yearbook of County Water Supply*. These data provided the remaining quantity variables in Eq. 5, namely the unit water treatment cost $\bar{c}$, the level of water supply $\tilde{z}$ and the value of fixed assets $\tilde{\boldsymbol{x}}_{\boldsymbol{2}}$. Each observation in these yearbooks refers to a water supply firm, which may own multiple water treatment works. This has added to the difficulty of performing the analysis at the water treatment work level. Moreover, many water supply firms were renamed (even more than once) due to reorganisation, acquisition and expansion etc. over the 24-year-long time span of this study. Therefore, I have opted to conduct the analysis at the county level to circumvent the uncertainties around identifying the same water supply firms under different names. I thus aggregated the land use, rainfall, water supply and asset variables to the county level, and derived the county level unit water treatment cost variable as each county's total treatment cost divided by its total water supply. In fact, these 'aggregated' observations still mostly contain firm-level information, since only a very small proportion (less than 7%) of the counties in my dataset have multiple water supply firms in one year. Turning to the prices of variable inputs and production assets ($\boldsymbol{w_1}$ and $\boldsymbol{w_2}$), the wage rate (or the price of labour) was measured at the county level using data from the *Sichuan Statistical Yearbook*, whereas the prices of raw water, electricity, chemicals and production assets were controlled for by year fixed effects, which will be further discussed in Section 3. In addition, the privatisation of China's urban water supply, as opposed to public management, has been expected to enhance the sector's performance in terms of cost-effectiveness (Jiang & Zheng, 2014; Li, 2018). I have therefore controlled for the proportion of private water supply firms in estimating the water treatment cost function. Panel 1 of Table 1 describes these variables, although for brevity it contains land cover and rainfall variables only for the 3km radius as an example, since the preferred regression models did not find a statistically significant effect of forest cover beyond the 3km radius on water treatment costs. Table A1 in Appendix I fully describes land cover and rainfall variables for all different radiuses involved in the regression analysis.

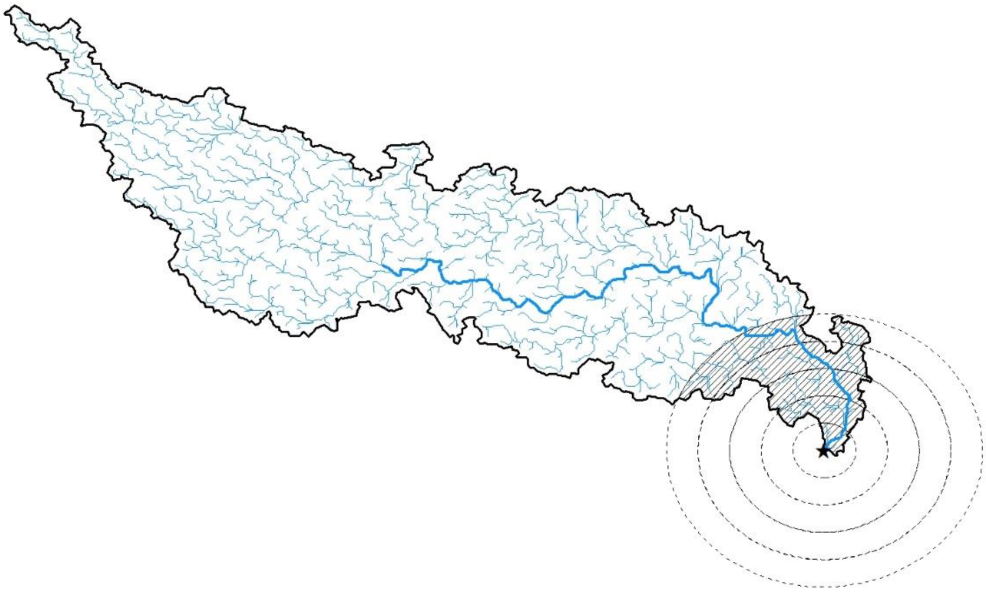


Figure 2: Schematic Diagram of a Water Intake Point and its Catchment

Table 1: Definition and Description of Variables

	Mean	SD	5% quantile	95% quantile
Panel 1: Variables in the water treatment cost function (county level, obs. = 1,618)				
Unit water treatment cost (CNY/m^3)	1.07	0.65	0.25	2.34
Forestland (%), inside catchment, 0km–3km	18.82	25.04	0	77.31
Forestland (%), outside catchment, 0km–3km	14.71	19.50	0	58.44
Cropland (%), inside catchment, 0km–3km	43.69	29.91	0.55	91.24
Urban areas (%), inside catchment, 0km–3km	5.49	11.44	0	26.11
Water supply (1mln m^3/yr.)	15.83	50.55	0.84	41.93
Wage rate (CNY 1k/yr.)	23.79	19.51	3.11	61.71
Pct. of private water supply firms	27.88	28.80	0.00	80.00
Rainfall 0km–3km (mm/yr.)	984.46	148.80	720.64	1214.00
Panel 2: Variables in the Heckman correction (obs. = 4,080)				
Ethnic minority autonomous county (binary: 0 = no; 1 = yes)	0.30	0.46	0	1
Distance to Chengdu (km)	223.86	126.00	57.78	474.82
Urban population (1k people)	87.09	84.30	5.30	242.00
Number of phones per capita	0.31	0.38	4.29×10^{-3}	1.03
Road density (km/km^2)	0.65	0.70	0.06	1.85
Percentage of private water works	23.07	29.16	0.00	80.00

Note: CNY 6.62 = USD 1 in 2018 prices.

3. Estimation Methods and Results

Figure 3 visualises the spatial distribution of unit water treatment cost levels and forest cover within a 3km radius upstream of the water intake point.[6] The two maps exhibit a reasonably distinguishable negative association between the two variables: unit water treatment costs tend to be higher (darker areas in Figure 3a) where water intake points are surrounded by less forest cover (lighter areas in Figures 3b), such as the dashed square areas. In the opposite direction, water treatment costs appear to be lower where water intake points have more forested buffers, such as the dashed circular areas. This pattern is suggestive of the postulated water purification effect of forests. Yet, the strength of such evidence is rather limited, as the observed spatial heterogeneity of water treatment costs might be induced by certain unobserved factors other than forest cover. For example, less forested locations might imply higher levels of urbanisation and hence higher prices of labour, in which case the observed higher water treatment costs in these places might be caused by higher labour costs instead of lower source water quality associated with less forest cover. These patterns will be further tested via the more rigorous regression analysis reported below.

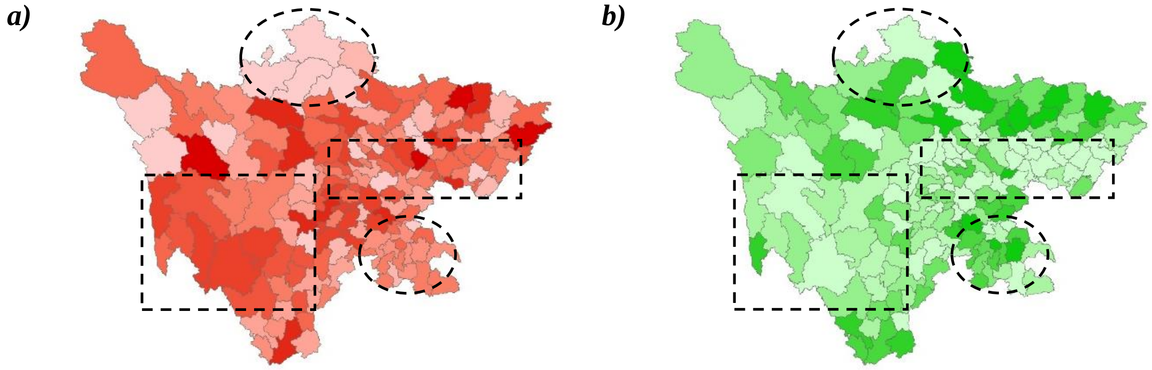


Figure 3: Spatial Distribution of Drinking Water Treatment Cost and Forest Cover

Note: a) unit water treatment cost (CNY/m^3, CNY 6.62 = USD 1 in 2018 prices); b) percentage of forestland 0km–3km upstream.

The departure point of my regression analysis is a county-level fixed effects model specified as per the water treatment cost function (Eq.5). This specification explicitly contains the following explanatory variables: the level of annual water supply, the wage rate, the percentage of private water works, the percentages of different land use types, and the linear and quadratic forms of annual rainfall at different distances of the water intake point. In

[6] Forest cover maps for other radiuses up to 10km (which are available upon request) have similar spatial patterns. It is difficult to visually assess whether forest cover in different radiuses have different spatial correlations with water treatment costs. Figure 3 therefore focuses on forest cover in the 3km radius as an example, for the same reason as in Table 1.

particular, runoff from cropland and urban areas tends to carry considerable amounts of agricultural fertilisers and household sewage, which is likely to induce higher water treatment costs. On the other hand, these land use types are often converted from natural land cover such as forests, and therefore may have a negative correlation with the percentage of forest cover. I thus explicitly controlled for the percentages of cropland and urban areas to avoid potential confounding bias.[7] Moreover, I attempt to account for other price variables using year fixed effects. Prices of raw water and electricity are regulated to be identical throughout the province in a given time period. Chemicals (such as clarifying agents and disinfectants) and production assets are likely to be purchased from a single and sufficiently competitive market. I thus assume that prices of chemicals and production assets vary over time but not across water treatment works. These year fixed effects also control for a variety of other time varying factors that are homogeneously faced by all water treatment works, such as inflation and changes in national and provincial environmental and resource policies. In addition, this specification includes county fixed effects to eliminate potential confounding factors that are county specific but do not vary over time, such as various topographical and geological characteristics. Standard errors are clustered at the county level to address unobserved within-county correlation (Cameron & Miller, 2015). Lastly, the logarithmic transformation is approximated using the inverse hyperbolic sine (IHS) transformation, which allows zero values of the land use variables. All estimates are expressed as elasticities derived using the approach recommended by Bellemare and Wichman (2019).[8]

Figure 4a presents the estimated elasticities of the unit water treatment cost with respect to forest cover within different radiuses upstream from the water intake point, where the solid line represents the point estimates and the dashed lines give the confidence intervals at the 1%, 5% and 10% significance levels. These estimates were derived from 10 regression models that each contain a single forest cover variable for a certain radius, as exemplified by Model 1 in Table 2. The expected cost saving effect attributable to forests' water purification services is statistically confirmed for forests within 3km upstream, as the estimate for this radius has a confidence interval (at the 10% significance level) entirely below zero. The estimate for the 4km radius is statistically significant at the 10% level as well, although the *p*-

[7] I also investigated the locations of 175 wastewater treatment plants in Sichuan province which are routinely monitored by the state as major sources of water pollution ('guokong' plants). Of the 170 counties involved in this study, only three have a single 'guokong' wastewater treatment plant within 10km upstream of their drinking water intake points. Dropping these three counties led to qualitatively similar findings. (Full regression results are available upon request.) Alternatively, due to lack of time-variant data on these wastewater plants (e.g. the time they started operating and the volume of wastewater treated/discharged every year), the only control variable that could be constructed using the locations of these wastewater plants would be a time-invariant variable indicating the number of wastewater plants located upstream of each county's drinking water intake points, which has already been accounted for by county fixed effects and hence would not affect the estimates regardless of whether they are added to the regression models.

[8] Following Bellemare and Wichman (2019), the original values of all the variables listed in Panel 1 of Table 1 were multiplied by 100 before the IHS transformation to obtain stable elasticity estimates. This adjustment did not change the signs and statistical significance of the elasticity estimates.

value goes slightly above 10% after correcting for the unbalanced panel dataset, which will be further discussed shortly. I have thus opted to focus on the estimate for the 3km radius (for the moment) and report in Table 2 the full estimates for the corresponding model (Model 1). In contrast, estimates for larger radiuses up to 10km upstream, albeit still negative, are statistically equal to zero, since all their confidence intervals encompass the zero axis. As mentioned above, forests in farther upstream locations are less likely to influence water quality at the water intake points. That said, it is worth noting that the estimate for the closest radius (1km) is statistically insignificant as well. This is likely because the catchment segments within this radius tend to be small in my dataset (sample mean[9] = 3km^2), which may therefore have a less discernible effect on water treatment costs. In comparison, the area of the 3km radius segments is much larger (sample mean = 20km^2), which may allow more contact between surface runoff and forests. Comparing Figures 4a and A1a in the appendix, I have qualitatively similar findings regardless of whether forest cover is measured in percentages or area units.

As can be seen in Model 1, the magnitude of the estimate for the variable 'IHS of percentage of forestland 0km–3km' implies that a 1% increase in forest cover within a 3km radius upstream from the water intake point would decrease drinking water treatment costs by almost 0.02% (at the means of the two variables). Another way to interpret this elasticity estimate is that a 1km^2 increase in forest cover would reduce water treatment costs by CNY 0.006/m^3 (USD 0.001/m^3). This is much smaller than the elasticity estimates reported by Singh and Mishra (2014) and Vincent et al. (2016) in the contexts of India and Malaysia respectively, but comparable to those by a French and a Portuguese case study [i.e. Abildtrup et al. (2013) and Lopes et al. (2019)]. It appears that forests in the tropics help reduce drinking water treatment costs to a greater extent than those in higher latitude regions, although the evidence base needs to be further augmented to substantiate this conjecture. The aggregate cost savings derived using the total water supply in 2018 amount to CNY 63mln (USD 9.5mln). This value, although lower than the province's forest investments in the same year, is provided by a small proportion of the province's forests (those within 3km upstream of drinking water intake points). Moreover, such benefits will continue to accrue in increasing amounts over time, in light of the ongoing rapid urbanisation of Sichuan province and the accompanying expansion of municipal water supply.

[9] This refers to the mean of the county-level data, where each observation may represent the total area of multiple catchment segments corresponding to several water intake points.

Table 2: Estimated Water Treatment Cost Function using Land Cover Percentage Variables

Dependent variable: IHS of unit cost **Explanatory variables:**	**Model 1**	**Model 2**	**Model 3**
IHS of pct. of forestland 0km–3km	***–1.84×10⁻²****		
(inside catchment)	***(9.53×10⁻³)***	***(1.01×10⁻²)***	
IHS of pct. of forestland 0km–3km			0.16
(outside catchment)			(0.47)
IHS of pct. of cropland 0km–3km	1.54×10^{-2}	1.85×10^{-2}	2.36×10^{-2}
(inside catchment)	(2.28×10^{-2})	(2.36×10^{-2})	(2.45×10^{-2})
IHS of pct. of urban area 0km–3km	1.72×10^{-2}	1.66×10^{-2}	1.73×10^{-2}
(inside catchment)	(1.22×10^{-2})	(1.22×10^{-2})	(1.21×10^{-2})
IHS of rainfall 0km–3km	5.40	5.43	5.31
	(8.16)	(8.12)	(8.16)
Squared IHS of rainfall 0km–3km	–0.22	–0.23	–0.22
	(0.34)	(0.33)	(0.34)
IHS of water supply	***–0.20****	***–0.21****	***–0.21****
	(0.04)	***(0.04)***	***(0.04)***
IHS of wage rate	2.54×10^{-3}	-6.51×10^{-3}	4.00×10^{-3}
	(0.08)	(0.08)	(0.08)
IHS of pct. of state owned water works	6.73×10^{-3}	5.38×10^{-3}	5.39×10^{-3}
	(5.89×10^{-3})	(5.81×10^{-3})	(5.78×10^{-3})
Inverse Mills Ratio		***–0.78****	***–0.79****
		(0.29)	***(0.29)***
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Clustered standard errors (at the county level)	Yes	Yes	Yes
Number of observations	1,618	1,618	1,618
Model significance (p-value)	0.00	0.00	0.00
R^2 (within)	0.75	0.75	0.75

Note: Estimates that are statistically significant in both models are highlighted in bold italics (up to the 10% significance level). Asterisks indicate statistical significance: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01. Standard errors are in parentheses.

Nonetheless, my county level panel dataset is still unbalanced, which might bias the estimates if certain types of counties are more likely to have missing data, in which case the available observations with complete information would become an unrepresentative sample of the study area. For instance, the complete observations in my dataset have an average urban population of 110.66 thousand, which is notably higher than that of incomplete and missing observations (71.60 thousand), and the difference is strongly significant with a p-value below 0.001. This implies that counties with a smaller urban population are more likely to have missing data; this is not surprising because water supply firms smaller than a threshold size (probably serving a smaller urban population) are not legally obliged to report to statistics authorities. As can be seen in Model 1, the negative and statistically significant estimate on the variable 'IHS of water supply' suggests that counties with a higher scale of water supply (which is likely associated with a larger urban population) tend to have lower unit water treatment costs. Therefore, the complete observations in my dataset are likely to underestimate the province's unit water treatment costs, since counties with a smaller urban population (and hence potentially a smaller scale of water supply and higher unit water treatment costs) are more likely to be missing. There are similar yet more subtle implications for the estimates on forest cover. If the available observations constitute an unrepresentative sample of the province, it would be possible that the estimated water purification effect of forests deviates from the overall situation of the province.

I performed a Heckman correction following a two-stage procedure described by Wooldridge (2010) to formally assess whether the estimates in Model 1 are indeed biased due to missing data. The first stage is a probit sample selection equation (Model 4 in Table 3) estimated using the regressors listed in Panel 2 of Table 1 for the entire sample (170 counties × 24 years = 4,080 observations). The variable 'urban population' captures the scale-dependent obligation of statistical reporting mentioned above. In addition, I included several variables that account for communication costs within a centralised economic system, as per Huang et al. (2017). These variables include each county's distance to the capital city of the province (Chengdu), number of phones per capita, road density and percentage of private water works. Furthermore, the first-stage model contains a binary variable that indicates whether a county is an ethnic minority autonomous county, as China's ethnic minority autonomous divisions are typically less integrated with the country's governing system (Han & Paik, 2017) and therefore may be less responsive to the centralised statistical bureaucracy. These variables were obtained from the *Sichuan Statistical Yearbook* and hence were available for the entire sample. Lastly, I estimated the inverse mills ratio from the sample selection equation and inserted it into the water treatment cost function estimated using the selected sample.

Table 3: Estimated Probit Sample Selection Equation

Dependent variable: Water treatment data observed **Explanatory variables:**	**Model 4**
Ethnic minority autonomous county	***–0.51******
	(0.06)
Distance to Chengdu	***-5.89×10^{-4}******
	(2.06×10^{-4})
Urban population	***1.65×10^{-3}******
	(3.42×10^{-4})
Number of phones per capita	***–0.13****
	(0.07)
Road density	***0.06****
	(0.04)
Percentage of private water works	***1.32×10^{-3}****
	(7.55×10^{-4})
Number of observations	4,080
Model significance (*p*-value)	0.00
McFadden's R^2	0.07

Note: Estimates that are statistically significant in both models are highlighted in bold italics (up to the 10% significance level)
Asterisks indicate statistical significance: **p*-value < 0.10, ***p*-value < 0.05, ****p*-value < 0.01. Standard errors are in parentheses

Returning to Table 2, the second column of results (Model 2) presents the selection-corrected estimates of the water treatment cost function that contains forest cover within a 3km radius upstream. The statistically significant coefficient on the inverse mills ratio term provides corroborating evidence of the conjectured sample selection bias associated with missing data. However, the consequences of such bias for this particular model are somewhat limited, as the selection-corrected estimates on other regressors mostly closely resemble the uncorrected estimates in Model 1. In particular, there is no substantial change in the estimate for the variable 'IHS of percentage of forestland 0km–3km', although its statistical significance becomes slightly weaker. Figure 4b reports the selection-corrected estimates for forests at other distances. As mentioned above, the 4km radius estimate becomes statistically insignificant, since the upper bound of its 10% level confidence interval goes above zero. Aside from that, there is still no evidence that forests at farther distances have a statistically distinguishable effect on water treatment costs. Therefore, the previous findings and interpretation pertaining to the monetary value of forests' water purification services remain largely robust.

Furthermore, I conducted a placebo or falsification test in an attempt to examine whether the foregoing findings stem from some unobserved time-varying factors that are systematically correlated with variation in forest cover. In this test, I replaced the forest cover variable in the water treatment cost model using forests inside the same radius but outside the catchment area (the unshaded portions of the buffers in Figure 2). These out-of-catchment forests are either downstream from the water intake point or belong to another drainage system, and therefore, intuitively, should have no direct implications for water quality at the intake point. If there exist certain unobserved local factors that covary with both forest cover and water treatment costs, these factors would likely be correlated with forests inside and outside the catchment alike. In that case, regressing water treatment costs against out-of-catchment forests would (falsely) pick up a significant effect as well. Reassuringly, the estimates of the placebo regressions, which are statistically insignificant throughout all radiuses (as shown in Figure 4c), ease this concern to some extent. Admittedly, the estimates for out-of-catchment forests are not negligible in size relative to those for within-catchment forests. In particular, the negative estimate on out-of-catchment forests in the 2km radius suggests that higher levels of out-of-catchment forest cover correlate with lower water treatment costs, which cannot be explained by forests' water purification effect and is hence likely confounded by certain unobserved factors. In that case, the estimates on within-catchment forests in the 2km radius (as shown in Figures 4a and 4b) are likely subject to similar bias and should be taken with caution, since these estimates have likely overestimated forests' water purification effect. In contrast, the positive estimate on out-of-catchment forests in the 3km radius implies that the estimates on within-catchment forests in the same radius have likely underestimated forests' water purification services due to omitted factors. This is another reason that I opted to focus on estimates for the 3km radius (rather than those for the 2km radius which have higher magnitudes and statistical significance levels), since conservative estimates help reduce Type I error (or false positive findings) and are thus preferable for statistical hypothesis testing.

In addition, I formally assessed the implications of potential heterogeneity in the quality of treated water. Drinking water supply firms in China are required to treat water to the same set of national standards, and the quality of treated water is subject to routine self-monitoring and government inspections. Despite that, these standards and regulations tend to be loosely enforced, and the quality of treated water is likely to vary across regions. This is because economic growth is geographically unbalanced throughout the country, and less developed regions tend to have financial difficulties treating drinking water to the national standards, since treating drinking water to higher quality usually incurs higher treatment costs (Browder et al., 2007; Jiang & Zheng, 2014; Li, 2018). If these less developed regions are also less urbanised and therefore have higher levels of forest cover, omitting the quality of treated water in the regression analysis would confound the estimate on forest cover. My dataset contains water supply firms' self-reported percentage of tested water samples that achieve the quality standards, which shows some degree of heterogeneity: this percentage ranges from 80.71% to 100%, yet is above 98% for 90% of the observations that contain complete information for the regression analysis. Grieco and McDevitt (2017) developed a novel form of the production function which accounts for both the quantity and quality of output. As described in Appendix II, this model basically assumes that producing the same amount of output with higher quality requires a higher level of aggregate production input. This production function allows the quality of treated water to be explicitly controlled for in the regression models as an explanatory variable. I next re-estimated all regression models controlling for the quality of treated water, and the estimates turned out to be largely stable, as can be seen in Appendix II. Admittedly, my data on the quality of treated water were self-reported by water treatment firms and hence may not fully reflect the actual variation in quality. Despite that, the placebo test mentioned above has implicitly accounted for unobserved heterogeneity in the quality of treated water: if it has a substantial confounding effect (jointly with other unobserved factors), this should have been captured by the estimates for out-of-catchment forest cover.

Finally, the estimated elasticity of the unit water treatment cost with respect to the scale of water supply is negative and less than one in both Models 1 and 2. This implies that the unit water treatment cost decreases less than proportionally with the scale of water supply, or in other words, the water supply firms in my dataset exhibit increasing returns to scale.

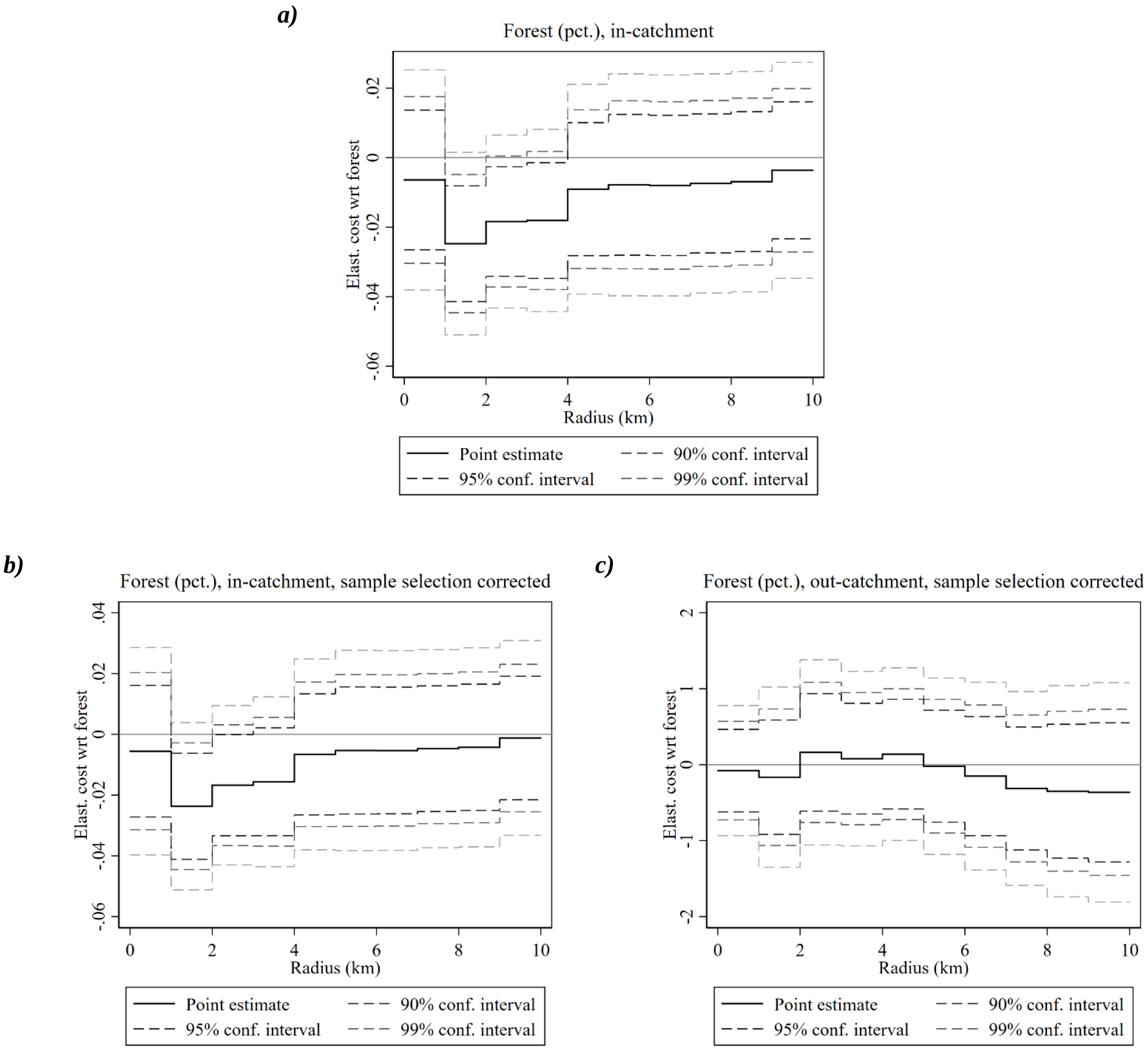


Figure 4: Elasticity Estimates with Respect to Forestland Percentages within Different Radiuses

4. Discussion and Conclusions

This study robustly measures the monetary value of forests' water purification services in the form of the ensuing cost savings of municipal drinking water treatment. This was enabled by a rich panel dataset from China's Sichuan province, which allowed me to adopt the fixed effects approach to control for a variety of observed and unobserved factors that might otherwise have biased the estimates of interest. This study thus adds to the currently thin formal econometric evidence base in this regard, which is recently reviewed by Price and Heberling (2018) and typically represented by the study of Vincent et al. (2016). Moreover, this study has undertaken a novel spatial piecewise approach to investigate the spatial patterns of such cost savings delivered by forests in different segments of the catchment area. This approach finds statistically significant evidence that substantiates the expected cost saving effect of forests only inside a 3km radius upstream from each water intake point. This finding provides suggestive practical implications for the optimal spatial targeting of forest conservation efforts.

The aggregate water treatment cost savings delivered by forests in the study area amount to CNY 63mln (USD 9.5mln) in 2018. This value is only moderate relative to the scale of the province's economy and forest investments. However, the primary contribution of this study is to demonstrate the spatial piecewise approach, which helps identify the heterogenous water purification services provided by forests at various distances from the water intake point. This approach also facilitates a placebo test utilising out-of-catchment forest cover in the same radius of the water intake point, which provides important insights as to the direction and magnitude of potential omitted variable bias. This methodological twist is transferrable and applicable to other regions where the optimal spatial targeting of forest conservation is particularly relevant, such as less developed tropical regions where local livelihoods tend to heavily rely on extraction of forest resources (which implies a higher opportunity cost of forest conservation). Moreover, forests' water purification services may provide other benefits aside from savings of drinking water treatment costs. For instance, in my study area, more than two-thirds of the province's population still rely on untreated water from natural sources. These untreated water users are likely to benefit from forests' water purification services in the form of reduced exposure to waterborne diseases (Herrera et al., 2017) etc. Yet such benefits are not captured by the production function approach in this study, which focuses on centralised drinking water treatment.

References

Abildtrup, J., Garcia, S., & Stenger, A. (2013). The effect of forest land use on the cost of drinking water supply: A spatial econometric analysis. *Ecological Economics*, *92*, 126–136. https://doi.org/10.1016/j.ecolecon.2013.01.004

Armsworth, P. R. (2014). Inclusion of costs in conservation planning depends on limited datasets and hopeful assumptions. *Annals of the New York Academy of Sciences*, *1322*(1), 61–76. https://doi.org/10.1111/nyas.12455

Bateman, I. J., Harwood, A. R., Mace, G. M., Watson, R. T., Abson, D. J., Andrews, B., … Termansen, M. (2013). Bringing ecosystem services into economic decision-making: Land use in the United Kingdom. *Science*, *341*(6141), 45–50. https://doi.org/10.1126/science.1234379

Bellemare, M. F., & Wichman, C. J. (2019). Elasticities and the Inverse Hyperbolic Sine Transformation. *Oxford Bulletin of Economics and Statistics*, *n/a*(n/a). https://doi.org/10.1111/obes.12325

Browder, G. J., Xie, S., Kim, Y., Gu, L., Fan, M., & Ehrhardt, D. (2007). *Stepping up: Improving the performance of China's urban water utilities*. Washington DC: The World Bank. https://doi.org/10.1596/978-0-8213-7331-6

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, *50*(2), 317–372. https://doi.org/10.3368/jhr.50.2.317

ESA Climate Change Initiative. (2017). Quick user guide of the Land Cover State products in GTiff and NetCDF formats. Retrieved from http://maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-QuickUserGuide-LC-Maps_v2-0-7.pdf

Ferraro, P. J., Lawlor, K., Mullan, K. L., & Pattanayak, S. K. (2012). Forest gigures: Ecosystem services valuation and policy evaluation in developing countries. *Review of Environmental Economics and Policy*, *6*(1), 20–44. https://doi.org/10.1093/reep/rer019

Freeman, A. M. I., Herriges, J. A., & Kling, C. L. (2014). *The Measurement of Environmental and Resource Values: Theory and Methods* (3rd ed.). Oxford: RFF Press, Taylor & Francis.

Grieco, P. L. E., & McDevitt, R. C. (2017). Productivity and quality in health care: Evidence from the dialysis industry. *The Review of Economic Studies*, *84*(3), 1071–1105. https://doi.org/10.1093/restud/rdw042

Greenstone, M., & Gayer, T. (2009). Quasi-experimental and experimental approaches to environmental economics. *Journal of Environmental Economics and Management*, *57*(1), 21–44. https://doi.org/10.1016/j.jeem.2008.02.004

Han, E., & Paik, C. (2017). Ethnic integration and development in China. *World Development*, *93*, 31–42. https://doi.org/10.1016/j.worlddev.2016.12.010

Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology*, *34*(3), 623–642. https://doi.org/10.1002/joc.3711

Hellerstein, D. M. (2017). The US Conservation Reserve Program: The evolution of an enrollment mechanism. *Land Use Policy*, *63*, 601–610. https://doi.org/10.1016/j.landusepol.2015.07.017

Herrera, D., Ellis, A., Fisher, B., Golden, C. D., Johnson, K., Mulligan, M., … Ricketts, T. H. (2017). Upstream watershed condition predicts rural children's health across 35 developing countries. *Nature Communications*, *8*(1), 811. https://doi.org/10.1038/s41467-017-00775-2

Huang, Z., Li, L., Ma, G., & Xu, L. C. (2017). Hayek, local information, and Commanding heights: Decentralizing state-owned enterprises in China. *American Economic Review*, *107*(8), 2455–2478. https://doi.org/10.1257/aer.20150592

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, *47*(1), 5–86. https://doi.org/10.1257/jel.47.1.5

Jiang, Y., & Zheng, X. (2014). Private sector participation and performance of urban water utilities in China. *Economic Development and Cultural Change*, *63*(1), 155–189. https://doi.org/10.1086/677739

Li, L. (2018). Private sector participation and performance of county water utilities in China. *China Economic Review*, *52*, 30–53. https://doi.org/10.1016/j.chieco.2018.06.001

Lopes, A. F., Macdonald, J. L., Quinteiro, P., Arroja, L., Carvalho-Santos, C., Cunha-e-Sá, M. A., & Dias, A. C. (2019). Surface vs. groundwater: The effect of forest cover on the costs of drinking water. *Water Resources and Economics, Forthcoming*. https://doi.org/10.1016/j.wre.2018.06.002

Millennium Ecosystem Assessment. (2005). *Ecosystems and Human Well-being: Synthesis*. Washington, DC: Island Press.

National Bureau of Statistics of China. (2019). *China Statistical Yearbook 2019*. Beijing: China Statistics Press.

Osborn, T. J., & Jones, P. D. (2014). The CRUTEM4 land-surface air temperature data set: Construction, previous versions and dissemination via Google Earth. *Earth System Science Data*, *6*(1), 61–68. https://doi.org/10.5194/essd-6-61-2014

Pearce, D. (2004). Environmental market creation: Saviour or oversell? *Portuguese Economic Journal*, *3*(2), 115–144. https://doi.org/10.1007/s10258-004-0034-y

Polasky, S., Nelson, E., Camm, J., Csuti, B., Fackler, P., Lonsdorf, E., … Tobalske, C. (2008). Where to put things? Spatial land management to sustain biodiversity and economic returns. *Biological Conservation*, *141*(6), 1505–1524. https://doi.org/10.1016/j.biocon.2008.03.022

Price, J. I., & Heberling, M. T. (2018). The effects of source water quality on drinking water treatment costs: A review and synthesis of empirical literature. *Ecological Economics*, *151*, 195–209. https://doi.org/10.1016/j.ecolecon.2018.04.014

Singh, S., & Mishra, A. (2014). Deforestation-induced costs on the drinking water supplies of the Mumbai metropolitan, India. *Global Environmental Change*, *27*, 73–83. https://doi.org/10.1016/j.gloenvcha.2014.04.020

Song, X.-P., Hansen, M. C., Stehman, S. V, Potapov, P. V, Tyukavina, A., Vermote, E. F., & Townshend, J. R. (2018). Global land change from 1982 to 2016. *Nature*, *560*(7720), 639–643. https://doi.org/10.1038/s41586-018-0411-9

Tibesigwa, B., Siikamäki, J., Lokina, R., & Alvsilver, J. (2019). Naturally available wild pollination services have economic value for nature dependent smallholder crop farms in Tanzania. *Scientific Reports*, *9*(1), 3434. https://doi.org/10.1038/s41598-019-39745-7

United Nations Childrens Fund, & World Health Organization. (2019). *Progress on household drinking water, sanitation and hygiene 2000-2017. Special focus on inequalities.* New York: United Nations Childrens Fund and World Health Organization.

Vincent, J. R. (2011). Valuing the environment as a production input. In A. K. E. Haque, M. N. Murty, & P. Shyamsundar (Eds.), *Environmental Valuation in South Asia* (pp. 36–78). https://doi.org/10.1017/CBO9780511843938.004

Vincent, J. R., Ahmad, I., Adnan, N., Burwell, W. B., Pattanayak, S. K., Tan-Soo, J.-S., & Thomas, K. (2016). Valuing water purification by forests: An analysis of Malaysian panel data. *Environmental and Resource Economics*, *64*(1), 59–80. https://doi.org/10.1007/s10640-015-9934-9

Westling, N., Stromberg, P. M., & Swain, R. B. (2020). Can upstream ecosystems ensure safe drinking water—Insights from Sweden. *Ecological Economics*, *169*, 106552. https://doi.org/10.1016/j.ecolecon.2019.106552

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). Cambridge, Massachusetts and London, England: The MIT Press.

Wunder, S., Noack, F., & Angelsen, A. (2018). Climate, crops, and forests: a pan-tropical analysis of household income generation. *Environment and Development Economics*, *23*(3), 279–297. https://doi.org/DOI: 10.1017/S1355770X18000116

Appendix I

Table A1: Descriptive Statistics of Land Cover and Rainfall Variables in Different Radiuses

	Mean	SD	5% quantile	95% quantile
Forestland (%), inside catchment, obs. = 1,618				
0km–1km	14.11	23.91	0	67.44
0km–2km	16.71	23.97	0	68.97
0km–3km	18.82	25.04	0	77.31
0km–4km	20.54	25.53	0	84.06
0km–5km	21.91	25.94	0	82.81
0km–6km	22.58	26.16	0	82.21
0km–7km	23.12	26.42	0	79.91
0km–8km	23.97	26.72	0	76.30
0km–9km	24.57	26.98	0	75.85
0km–10km	25.20	27.30	0	76.19
Forestland (%), outside catchment, obs. = 1,618				
0km–1km	11.68	19.52	0	59.46
0km–2km	13.79	19.30	0	56.67
0km–3km	14.71	19.50	0	58.44
0km–4km	15.79	19.80	0	56.05
0km–5km	16.83	20.35	0	58.04
0km–6km	17.74	20.58	0	61.12
0km–7km	18.54	20.81	0	61.93
0km–8km	19.26	21.13	0	65.19
0km–9km	19.83	21.44	0.07	66.73
0km–10km	20.37	21.74	0.10	68.78
Cropland (%), inside catchment, obs. = 1,618				
0km–1km	43.40	30.75	0	93.75
0km–2km	43.86	29.48	0	93.18
0km–3km	43.69	29.91	0.55	91.24
0km–4km	43.57	30.32	0.61	92.12
0km–5km	44.00	31.01	0.47	93.40
0km–6km	44.49	31.43	0.45	94.18
0km–7km	45.15	31.75	0.45	94.87
0km–8km	45.28	31.96	0.45	94.60
0km–9km	45.33	32.15	0.45	94.66
0km–10km	45.15	32.35	0.38	94.98
Urban areas (%), inside catchment, obs. = 1,618				
0km–1km	7.61	14.73	0	36.07
0km–2km	5.77	11.38	0	26.63
0km–3km	5.49	11.44	0	26.11
0km–4km	4.80	10.04	0	21.64
0km–5km	4.15	9.02	0	20.41
0km–6km	3.60	8.13	0	17.48
0km–7km	3.17	7.37	0	14.04
0km–8km	2.83	6.74	0	12.59

0km–9km	2.51	6.15	0	10.98
0km–10km	2.30	5.76	0	10.68
Rainfall (mm/yr.), inside catchment, obs. = 1,618				
0km–1km	987.09	149.93	725.20	1,215.18
0km–2km	985.38	149.15	721.00	1,214.00
0km–3km	984.46	148.80	720.64	1,214.00
0km–4km	983.82	148.58	720.83	1,214.00
0km–5km	983.08	148.40	721.00	1,213.00
0km–6km	982.38	148.25	721.00	1,213.00
0km–7km	981.88	148.23	720.62	1,213.00
0km–8km	981.46	148.26	719.87	1,213.00
0km–9km	980.98	148.28	719.16	1,213.00
0km–10km	980.50	148.28	718.46	1,213.00

Table A2: Estimated Water Treatment Cost Function using Land Cover Area Variables

Dependent variable: IHS of unit cost	**Model A1**	**Model A2**	**Model A3**
Explanatory variables:			
IHS of forestland area 0km–3km	***-2.73×10^{-2}*****	***-2.61×10^{-2}*****	
(inside catchment)	***(1.21×10^{-2})***	***(1.27×10^{-2})***	
IHS of forestland area 0km–3km			0.15
(outside catchment)			(0.44)
IHS of cropland area 0km–3km	6.91×10^{-3}	7.23×10^{-3}	-1.31×10^{-2}
(inside catchment)	(2.61×10^{-2})	(2.73×10^{-2})	(3.34×10^{-2})
IHS of urban areas 0km–3km	1.94×10^{-2}	1.80×10^{-2}	1.57×10^{-2}
(inside catchment)	(1.33×10^{-2})	(1.32×10^{-2})	(1.27×10^{-2})
IHS of rainfall 0km–3km	5.60	5.66	5.65
	(8.10)	(8.06)	(8.11)
Squared IHS of rainfall 0km–3km	–0.23	–0.24	–0.23
	(0.33)	(0.33)	(0.33)
IHS of water supply	***–0.20******	***–0.21******	***–0.21******
	(0.04)	***(0.04)***	***(0.04)***
IHS of wage rate	2.54×10^{-3}	-6.45×10^{-3}	1.19×10^{-2}
	(0.08)	(0.08)	(0.08)
IHS of pct. of state owned water works	6.57×10^{-3}	5.21×10^{-3}	5.06×10^{-3}
	(5.93×10^{-3})	(5.85×10^{-3})	(5.83×10^{-3})
Inverse Mills Ratio		***–0.78******	***–0.78******
		(0.29)	***(0.29)***
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Clustered standard errors (at the county level)	Yes	Yes	Yes
Number of observations	1,618	1,618	1,618
Model significance (p-value)	0.00	0.00	0.00
R^2 (within)	0.75	0.75	0.75

Note: Estimates that are statistically significant in both models are highlighted in bold italics (up to the 10% significance level). Asterisks indicate statistical significance: **p*-value < 0.10, ***p*-value < 0.05, ****p*-value < 0.01. Standard errors are in parentheses.

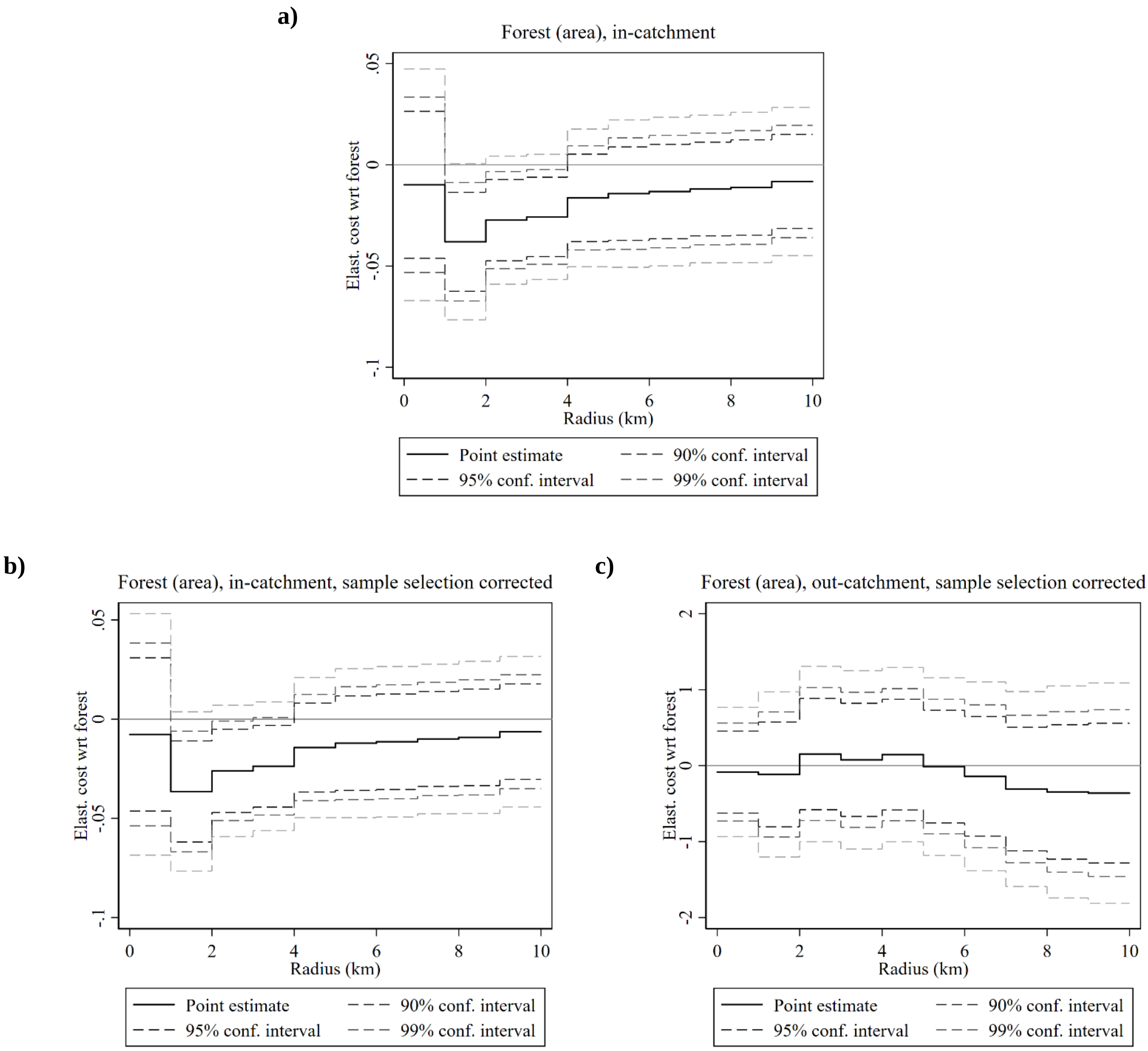


Figure A1: Elasticity Estimates with Respect to Forestland Area within Different Radiuses

Appendix II

I repeated the analysis using an alternative form of the production function which accounts for both the quantity and quality of output, following Grieco and McDevitt (2017):

$$zq^{\delta} = \boldsymbol{x_1^{\alpha} x_2^{\beta} e^{\gamma}}, \qquad \text{Eq.A1}$$

which basically assumes that producing the same amount of output z with higher quality q requires a higher level of aggregate production input.[10] It is assumed that the production process can be divided into separable and independent steps, where producers first decide the quantity and quality of output, and then in the next step decide the levels of production inputs. In that case, the cost function can be derived in the same manner as in Section 2, through solving a cost minimisation problem with predetermined levels of z and q:

$$\bar{c} = \frac{c}{\tilde{z}} = \frac{\boldsymbol{w_1} x_1^{*} + \boldsymbol{w_2} x_2^{*}}{\tilde{z}} = K\boldsymbol{w_1}^{\frac{\alpha}{\alpha+\beta}} \boldsymbol{w_2}^{\frac{\beta}{\alpha+\beta}} \boldsymbol{\tilde{e}}^{-\frac{\gamma}{\alpha+\beta}} \tilde{z}^{\left(\frac{1}{\alpha+\beta}-1\right)} \tilde{q}^{\frac{\delta}{\alpha+\beta}}, \qquad \text{Eq.A2}$$

which can be rewritten as the log linear form:

$$ln\bar{c} = lnK + \frac{\boldsymbol{\alpha}}{\boldsymbol{\alpha+\beta}} ln\boldsymbol{w_1} + \frac{\boldsymbol{\beta}}{\boldsymbol{\alpha+\beta}} ln\boldsymbol{w_2} - \frac{\gamma}{\boldsymbol{\alpha+\beta}} ln\boldsymbol{\tilde{e}} + \left(\frac{1}{\boldsymbol{\alpha+\beta}} - 1\right) ln\tilde{z} + \frac{\delta}{\boldsymbol{\alpha+\beta}} ln\tilde{q}. \qquad \text{Eq.A3}$$

The empirical implication is that this production function allows the quality of treated water to be explicitly controlled for in the regression models as an explanatory variable. I next re-estimated all regression models controlling for the quality of treated water, and the results are almost identical to those presented in the main text, as can be seen in Table A3 and Figure A2.

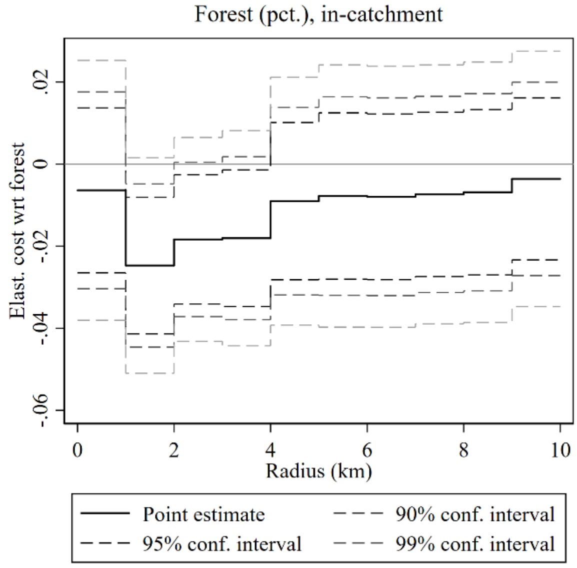
[10] Grieco and McDevitt (2017) described the production function in the log linear form: $lnz = \theta(\boldsymbol{\alpha} ln\boldsymbol{x_1} + \boldsymbol{\beta} ln\boldsymbol{x_2} + \boldsymbol{\gamma} ln\boldsymbol{e})$, and $lnq = \frac{1-\theta}{\delta}(\boldsymbol{\alpha} ln\boldsymbol{x_1} + \boldsymbol{\beta} ln\boldsymbol{x_2} + \boldsymbol{\gamma} ln\boldsymbol{e})$, where the parameter θ distinguishes the proportions of aggregate input used to produce the quantity and quality of output. It can be seen that the production function described in Eq. A1, after taking the logarithm of both sides, would be equivalent to the model proposed by Grieco and McDevitt (2017). I expressed the production function in the original Cobb-Douglas functional form (instead of the log linear form) to facilitate the derivation of the cost function.

Table A3: Estimated Water Treatment Cost Function using Land Cover Percentage Variables and Controlling for the Quality of Treated Water

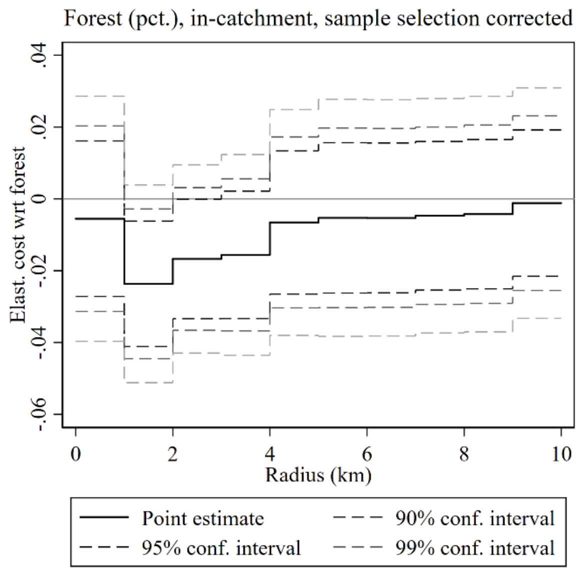
Dependent variable: IHS of unit cost **Explanatory variables:**	**Model A4**	**Model A5**	**Model A6**
IHS of pct. of forestland 0km–3km	***-1.83×10^{-2}****	***-1.67×10^{-2}****	
(within catchment)	***(9.52×10^{-3})***	***(1.00×10^{-2})***	
IHS of pct. of forestland 0km–3km			0.16
(out of catchment)			(0.47)
IHS of pct. of cropland 0km–3km	1.53×10^{-2}	1.85×10^{-2}	2.36×10^{-2}
(within catchment)	(2.29×10^{-2})	(2.37×10^{-2})	(2.45×10^{-2})
IHS of pct. of urban area 0km–3km	1.72×10^{-2}	1.66×10^{-2}	1.73×10^{-2}
(within catchment)	(1.22×10^{-2})	(1.22×10^{-2})	(1.21×10^{-2})
IHS of rainfall 0km–3km	5.40	5.43	5.31
	(8.16)	(8.12)	(8.16)
Squared IHS of rainfall 0km–3km	–0.22	–0.23	–0.22
	(0.34)	(0.33)	(0.34)
IHS of water supply	***–0.20****	***–0.21****	***–0.21****
	(0.04)	***(0.04)***	***(0.04)***
IHS of wage rate	2.90×10^{-3}	-6.23×10^{-3}	4.30×10^{-3}
	(0.08)	(0.08)	(0.08)
IHS of pct. of state owned water works	6.74×10^{-3}	5.40×10^{-3}	5.41×10^{-3}
	(5.91×10^{-3})	(5.83×10^{-3})	(5.80×10^{-3})
IHS of quality	0.09	0.07	0.08
	(1.24)	(1.28)	(1.28)
Inverse Mills Ratio		***–0.78****	***–0.79****
		(0.29)	***(0.29)***
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Clustered standard errors (at the county level)	Yes	Yes	Yes
Number of observations	1,618	1,618	1,618
Model significance (p-value)	0.00	0.00	0.00
R^2 (within)	0.75	0.75	0.75

Note: Estimates that are statistically significant in both models are highlighted in bold italics (up to the 10% significance level). Asterisks indicate statistical significance: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01. Standard errors are in parentheses.

a)



b)



c)

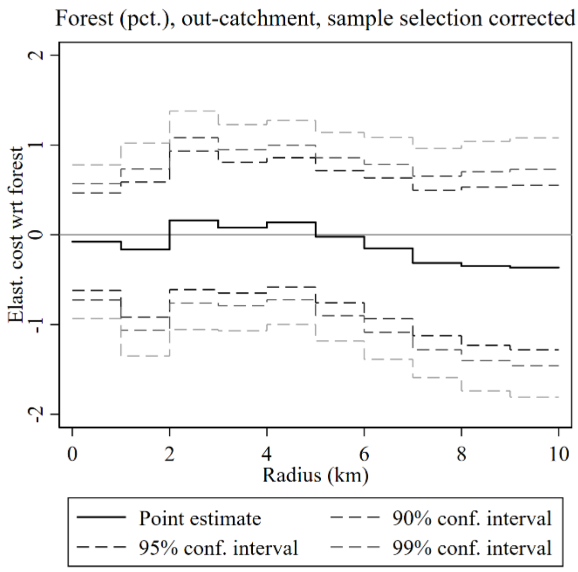


Figure A2: Elasticity Estimates with Respect to Forestland Percentages within Different Radiuses Controlling for the Quality of Treated Water