Agricultural land deals in Liberia undermine local households' access to lands and forests

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Abstract: The evidence on the impacts of agricultural land deals on local households' livelihoods is mixed. Using unique household survey data collected in 2018 in Liberia, we estimate the effects of land concessions for commercial agricultural production of palm oil, rubber, and cocoa on various livelihood indicators by comparing affected and non-affected towns. We find evidence supporting decreased access to agricultural land (9-12%) and community forest land (21%) due to concession operations, which led to greater food insecurity with decreases in the number of crops produced and non-timber forest products for subsistence. The reduction in access to lands and forests led to a decline in the average number of working hours (by 4.9 hours) in agricultural production. We also find that the number of out-migrants increased by 0.63 with a 14% increase in households receiving remittances in affected towns, which households used as a coping mechanism to offset the decrease in income.

Keywords: agricultural concessions, large-scale land transactions, impact evaluations, labor allocation, migration

JEL Codes: Q56, Q15, Q24

Introduction

Concession of land use rights through land deals is considered to be one of the major pathways for economic development in many low-income countries. Land deals increase tax revenues for the government, which can be used to encourage infrastructural developments such as roads and improve local livelihoods. The development of land for agricultural production through land deals could also provide employment opportunities for local labor forces and transfer the knowledge and technology that would not have been available previously for improved agricultural production and income. With these expectations, global land deals have increased significantly in the last two decades, with an estimated total size of concluded land deals to be 68 million hectares, comparable to the total area of Texas (Land Matrix 2021).

Local welfare impacts of land deals can be closely linked to the literature on the 'resource curse.' This literature found a pattern where resource-rich countries have experienced slower economic growth compared to resource-poor countries. This indicates that land deals might not lead to increased welfare, especially when combined with the lack of good institutions and policies to enforce rules and regulations in the process of land development (Frankel, 2010). Studies have found negative economic impacts such as decreased livelihoods, including income, food security, health, and education, due to land deals for natural resource extraction and agricultural production (e.g., Edwards, 2016; Shete and Rutten, 2015). On the other hand, positive impacts of land deals have also been found using household survey data for such outcomes as income, employment, consumption, and poverty rates (e.g., Aragón and Rud, 2013; Deininger and Xia, 2016; Jung et al., 2019).

In this paper, we study the impacts of land deals for commercial agricultural production on local livelihoods using theoretical predictions and unique household survey data collected in

2018 in Liberia. We focus on changes in households' access to land for subsistence crop production and access to forests that directly affect rural households' livelihoods. We investigate changes in labor allocations as a mechanism that influence households' livelihoods through theoretical and empirical models. While more evidence exists on the impacts of land deals for the extraction of natural resources in the economics literature, including forestry, mineral, and oil resources, there is less evidence on how concession of lands for commercial agricultural production has local economic implications (Jung, 2018). Liberia is one of the world's poorest countries, with land deals of various forms such as forestry, agricultural, and other natural resources occupying over 45% of the land. Therefore, understanding how land deals for agricultural production affect livelihoods similarly or differently through changes in crop production, forest access, and labor allocations has significant policy implications.

We estimate the impacts of agricultural land deals on various outcome and mechanism indicators by comparing them between affected and non-affected towns. We first identify a list of affected and non-affected towns by land deals using a set of criteria in collaboration with local NGOs. Then we select non-affected towns that have similar characteristics to affected towns in terms of demographic, socioeconomic, and biophysical data using a propensity score and available public data sources. Using collected survey data for affected (treatment) and non-affected (control) towns, we estimate difference-in-differences (DID) and instrumental variable (IV) regressions. We utilize our recall questions before the implementation of land deals when running the DID estimation. We check the robustness of our results by checking the consistency of results using a variety of sets of indicators for livelihoods and labor allocations.

We find that households that live closer to land deals and have been affected by them have less cultivation area by 9-12% and less access to community forests by 21% than non-affected households after the implementation of land deals. These decreases in access to agricultural lands and forests decreased the number of major subsistence crops that households produce and the number of forest products, which worsened households' perceived food security. An estimated 80% more households in affected towns indicate that any member of their household was unable to eat healthy and nutritious food because of a lack of money, harvest, or other resources compared to those in control towns. Our comparison of households' labor allocations and the source of income between affected and non-affected towns suggests that households in the affected towns worked 4.9 hours less in the agricultural sector than those in the non-affected towns, driven by the decrease of self-employed agricultural activities. We also find suggestive evidence that agricultural concessions might have provided some casual employment opportunities, which might not have been enough to offset the decrease in the total employment in agricultural production. Finally, we find that concession operations have increased the number of migrants by 0.63, which increased the number of households receiving remittances by 14%.

Our quantitative evidence of the negative effects of land deals on cultivation areas and forest access indicates a critical need to safeguard resource access rights for towns affected by land deals. While the material well-being will likely be more valuable in the short term, access to land for cultivation and forests for the harvest of forest products provides means of living, which is more critical in the long term. Therefore, policies that aim to promote local livelihoods from land deals would need to consider and weigh these short-term and long-term gains/losses.

Existing evidence on the impacts of resource concessions

Low- and middle-income countries that host land deals for resource concessions expect them to provide new economic opportunities and benefits for the government and local communities. This expectation is common whether the concessions are for the extraction of natural resources or agricultural production. Some of the benefits from resource concessions include revenues for the central government through tax collection that can lead to infrastructure developments, e.g., roads, and the transfer of skills and technology from concessionaires (Jung, 2018). At the local level, households living around concessions might enjoy benefits from increased economic activities such as increased employment and access to goods and services and the adoption of new technologies. The economics literature since the early 20th century has primarily focused on the relationship between natural resource extraction, foreign direct investments, and economic development, establishing extensive evidence on macro- and microeconomic factors that lead to successful or unsuccessful development outcomes (Alfaro, 2017; Cust and Poelhekke, 2015; Frankel, 2010).

Concessions for natural resource extraction and agricultural production can have varying environmental and livelihood implications because of the difference in the process and the nature of resources being exploited. Concessions for commercial agricultural production involve the more intensive conversion of existing land covers such as forest and savannah to agricultural land and use of it. Therefore, agricultural concessions are more likely to significantly impact local people's access to agricultural land, forest, and water for subsistence, food security, and farming-related activities such as input use and adoption of farming practices. Compared to the economics literature focusing on concessions for resource extraction, studies in other social and sustainability science literature have investigated the impacts of the so-called "global land rush" or "land grabbing" more broadly. These studies have had a more balanced exploration of both types of concessions for natural resource extraction and agricultural production, using qualitative and quantitative methods (e.g., Cotula et al., 2014; Hall et al., 2017; Holmén, 2015).

We find that studies based on individual case studies using qualitative methods provide an in-depth understanding of the local contexts and show more evidence of the negative livelihood impacts of agricultural concessions. Other studies with a broader spatial scale (e.g., multi-sites, nationwide, or multi-country) using quantitative data and methods provide more general understanding of impacts and find mixed impacts with some evidence of positive livelihood impacts resulting from agricultural concessions (Jung 2018). Some of the negative impacts include loss of access to community water and forest lands for subsistence and livelihoods, increased conflicts, decrease in income, soil depletion, biodiversity loss, loss of local crops and trees due to poorly contained fires used for land clearing as a result of agricultural concessions (Shete and Rutten, 2015; McDougal and Caruso, 2016; Papworth et al., 2017). A recent investigation of the impacts of agricultural concessions in 39 countries finds that agricultural concessions led to increased production of energy-rich crops for exports, undermining local food security in Asia and sub-Saharan Africa (Müller et al., 2021). In contrast, some positive spillover effects from agricultural concessions include increased access to inputs, adoption of new farming practices, and increased income from wage labor (Deininger and Xia, 2016; Bottazzi et al., 2018). Ali and Deininger (2021) summarize that positive external impacts for smallholders can be obtained if concessionaires 1) do not compete for land and other natural resources with small farms, 2) increase labor demand and smallholders' productivity, and 3) are under institutional arrangements such as contract farming.

More specifically, evidence on the impacts of agricultural concessions in Liberia is mixed at best. Most studies are based on case studies of effects from a specific concession company, where they find more negative impacts that often outweigh some positive impacts. Some common findings from case study reports from NGOs include a significant delay in delivering promised local infrastructure development by concession companies. For example, Firestone argues for their rubber plantations, the oldest agricultural concession in Liberia, to have improved local housing, schools, and medical facilities that were promised to local communities (Firestone Liberia, 2021). The operation of one of the largest oil palm plantations by Golden Veroleum has been under heavy scrutiny. A study found negative impacts to local communities outweigh positive effects (Sync Consult Limited, 2016). Common negative impacts include losing access to lands and forests for subsistence and increased food insecurity by agricultural concession operations (Forest Peoples Programme, 2015; Global Witness, 2015).

While no published study has solely focused on the impacts of agricultural concessions on livelihoods in Liberia using quantitative in multiple sites, some have studied environmental and livelihood impacts of concessions for resource extraction or all types of concessions (inclusive of agricultural concessions). Jung et al. (2019) focus on the effects of the full implementation of forestry concessions and find general equilibrium impacts of increased demands in goods and services, rather than direct impacts such as increased employment from concessions, to be the primary driver that caused improvements in asset-based wealth. Others were broader in that they either focused on all concessions in Liberia or studied multiple countries, including Liberia. Bunte et al. (2018) find heterogenous impacts of concessions on nighttime light growth, which varies by the concession type and source of capital but no significant impacts from agricultural concessions. Liao et al. (2020) conduct a scenario analysis finding that the potential effects of the full implementation of agricultural concessions in Liberia, Cambodia, Ethiopia, and Peru on population, forest cover, and carbon emissions to be significant.

Land rights and agricultural concessions in Liberia

In Liberia, land rights can be acquired in two ways; statutory and customary land tenure systems. The Public Lands Law was passed in 1956, which provides a process for purchasing public land by effectively giving the government to sell customary land to concessionaires with the acquisition of documents such as a Tribal Certificate or Public Land Certificate (USAID, 2012). These documents need to be signed by appropriate authorities, including the tribes' local elder, town head, clan head, and paramount chief for land under customary rights or the county's land commissioner for county land (Liz Wily, 2007). However, there have been frequent and recurrent disputes over the management, jurisdiction, and control of land resources involving customary versus statutory rights because there was a general lack of clarification in land rights between the two (Unruh, 2009).

Liberia's statutory land tenure system, laws, policies, and practices have long excluded rural communities. Global investors seeking vast land areas for mining, plantation, or agriculture (primarily palm oil) and forestry concessions have dominated land use and management policies, squeezing populations into isolated enclaves of "project impacted communities." A new land law (Land Rights Acts (LRA)) which recognizes customary land tenure, was passed in 2018. The new land law and the existing community Rights Law (CRL), previously passed in 2009, coexist. While CRL regulates community forests for long-term growth, the LRA controls land tenure. When appropriately enforced, it would allow the rural communities to own their land under customary law. However, challenges remain, including further clarity on regulations and guidelines on transferring customary land to commercial interests (SDI, 2019).

The history of granting land-use rights to foreign private companies in Liberia goes back to 1926 for Firestone's rubber plantation and 1949-1959 for other rubber plantations. As of

2016, ten active agricultural concessions are operating in Liberia (Table 1). All foreign-owned concessions produce rubber and oil palm, while there is only one concession, Liberia Cocoa Corporation, owned by Liberians and produces cocoa. Agricultural concessions are spread across the country with some, such as Sime Darby and Golden Veroleum, spanning multiple counties.

Table 1. Active agricultural concession operations in Liberia: crop type, the origin of the company, investment size, contract date, and county

Name	Crop	Origin	Investment size	Contract date	County
Cocopa Nimba Development Corporation	Rubber	Belgium	20M	1949	Nimba
Salala Rubber Corporation	Rubber	Belgium	36M	1959	Bong
Liberia Agriculture Corporation	Rubber	Belgium	87M	1957	Grand Bassa
Firestone Rubber Plantation	Rubber	U.S.	100M	1926/2005	Margibi
CRC: expanding in River Gee	Rubber	Ivory Coast	78M	2011	Maryland
Sime Darby	Oil palm	Malaysia	800M	2009	Bomi/Cape Mount/Gbarpolu
Maryland Oil Palm Plantation	Oil palm	Ivory Coast	64M	2011	Maryland
Golden Veroleum	Oil palm	Indonesia	1.6B	2010	Sinoe/Grand Kru
Equatorial Palm Oil	Oil palm	Equatorial Guinea	100M	2008	Grand Bassa
Liberia Cocoa Corporation	Cocoa	Liberia	12M	2014	Lofa

Similar to agricultural concessions in many other countries, a large share of contract area under agricultural concessions in Liberia is yet to be fully implemented by clearing land and planting commercial crops. Many of Liberia's existing spatially-explicit concession boundaries, such as those from the Global Forest Watch or Land Matrix, represent contract areas but not the areas where concessions have been fully in operation. Despite a large size that has not been fully implemented in many concessions, companies continue to negotiate with local communities to expand their contract area. For example, CRC has been operating in Maryland county since 2011 but continues to expand in River Gee county.

Conceptual framework

We build on Jessoe et al. (2018) and describe a simple household production and labor allocation model to illustrate how agricultural concessions can change labor allocations. We assume a one-person household and no land market for simplicity, and that household's aggregate utility is represented by a concave household utility function composed of consumption and leisure. A household maximizes the utility function:

$$U(c, l; \boldsymbol{Z})$$

,where *c* is the consumption for aggregate goods and non-assets, and *l* is leisure for a household; $\boldsymbol{Z}$ represents household-specific preferences. A household can use its own labor or hired labor for agricultural production. A household's concave agricultural production function is $F(L^{ag}, K)$, where each household uses its own (L^f) and hired labor (L^h), where $L^{ag} = L^f + L^h$, given the total available land for production, *K*. A household can provide its labor to the market (L^m) and hire labor (L^h) at the wage rate w. A household's extraction of natural resources from forests using its own labor (L^g) is $\delta G(L^g)$, where δ represents the quality of forest that affects the harvest of timber and non-timber forest products. The prices of consumption goods are assumed to be 1 for simplicity.

The utility function is subject to a budget constraint (*Y*) such that

$$Max_{c,l,L^f L^g \geq 0} U(c, l; \boldsymbol{Z})$$

$$s.t. \quad c = Y = \mathrm{F}(L^{ag}, A) - wL^h + \mathrm{w}L^m + \delta G(L^g)$$

$$L^{ag} = L^f + L^h$$

$$\mathrm{L^E} = L^f + L^m + L^g + l$$

$$c, l, L^f, L^m, L^h, L^g \geq 0$$

Therefore, solving for the first-order conditions, the demand for labor is determined by

$$L^{k*} = L^k(K, \delta, w, \boldsymbol{Z}), \qquad k \in \{f, g, h, m\} \tag{1}$$

This indicates that the labor demand for farming and extraction of natural resources depends on land (K), quality of forest (δ), market wage rate (w), and household-specific preferences ($\boldsymbol{Z}$). Maximizing utility subject to the income at optimal labor allocations $Y^* = \mathrm{F}(L^{f*} + L^{h*}, A) - wL^{h*} + \mathrm{w}L^{m*} + \delta G(L^{g*})$ derives demand for consumption:

$$c^*(w, Y^*). \tag{2}$$

The family labor supply (L^{F*}), which includes own agricultural production, labor supply to the market, and labor use for natural resource extraction, is the difference between the total amount of available time (L^{E}) and the demand for leisure:

$$L^{F*} = L^{f*} + L^{m*} + L^{g*} = L^{F*}(w, Y^*) = L^E - l^*. \tag{3}$$

Households that are labor buyers ($L^{m*} = 0, L^{h*} > 0$) or the demand for hired labor is

$$L^h(w, Y^*) = L^{ag*} - L^{F*} = L^{ag*} - (L^E - l^*). \tag{4}$$

Hypothesis 1. Agricultural concession operations decrease the total labor demand for agricultural production, wage labor, and extraction of forest resources if concession operations limit access to agricultural lands and forests.

Limited access to agricultural lands and forests of households in towns nearby concession areas serves as a channel through which agricultural concession operations decrease labor demand for agricultural production, wage labor, and extraction of forest resources. The decrease in the availability of land and forest for subsistence or commercial production, which has been documented in the literature (Jung, 2018), causes a reduction in demands for labor (L^f, L^{m}, L^g) through equation (1).

Hypothesis 2. Agricultural concession operations negatively impact demands for hired labor unless new hires created by concession operations offset them.

The supply of family labor to own agricultural production, wage labor, and extraction of forest resources (L^{F*}) increases as the income from the farm (Y^*) decreases (through equation (3)), assuming that leisure is a normal good. This increase in the supply of labor along with the decrease in income (Y^*) will decrease the demand for hired labor through equation (4).

Hypothesis 3. The decrease in labor demands caused by limited access to agricultural and forest lands imposed by agricultural concession operations (Hypothesis 1 and 2) increases labor migration.

The decrease in labor demands for agricultural production, wage labor, and forest resource extraction and the decline in access to agricultural and forest lands lead to a reduction in sources of income. Unless concession companies provide a significant amount of on-farm or off-farm opportunities, households affected by concessions will seek an alternative source of income. Migration is a tool that enables households to overcome market failures or volatilities in unstable economies as migrant-sending households receive remittances as rewards (Stark, 1991). Migration is further seen as a rational decision that allows stakeholders to hedge against risk and uncertainties (Abreu, 2012).

Identification strategy

Given the complexity of the old history and large extent of agricultural concessions but the limited area under active concession operations in Liberia, our identification strategy involves a selection of four concessions and 52 towns within and around those concessions. We use primary household surveys collected in 2018 to study the impacts of agricultural concessions in Liberia by the four concessions across four counties of Grand Bassa, Lofa, Maryland, and

Sinoe. We describe in detail the selection process of concessions, towns, and households in our survey.

Selection of four concessions

Among ten active agricultural concessions, we exclude four initially contracted concessions before 1970. Our survey includes households around four selected concessions that have been contracted since 2008, and we focus our analysis using households around these recently acquired concessions for the following reasons. First, our survey questions include socioeconomic changes after the arrival of concessions and recall questions before the arrival of concessions. It would be challenging for survey respondents to answer changes from over ten years before and remember their socioeconomic status more than ten years ago. Second, we use Liberia Census 2008 as our baseline demographic and socioeconomic characteristics (Table A1 in the Appendix) to reduce bias arising from the differences between affected and non-affected towns by matching them. Therefore, the inclusion of concessions contracted and operated before 2008 will bias the estimates because 2008 Census data already reflect changes resulting from the operation of concessions before 2008.

We select four concessions among six concessions that have been contracted since 2008 by considering the country of origin, crop type, and geographical location. We first choose Cocoa Liberia Corporation (LCC), the only Liberian company that produces cocoa. The rest of the five concessions are owned by foreign countries producing rubber and palm oil: Cavalla Rubber Corporation (CRC, Ivory Coast), growing rubber; Equatorial Palm Oil (EPO, Equatorial Guinea), Sime Darby (SD, Malaysia), Golden Veroleum (GVL, Indonesia), and Maryland Oil Palm (MOPP, Ivory Coast), producing palm oil. We then choose CRC due to its rubber production, unlike the other four concessions producing oil palm. Among four oil palm concessions, we choose GVL with the most significant investment size and EPO to increase variations in the country of origin. MOPP has not been selected due to its close proximity to CRC that has already been selected, and we had to exclude SD since there was a reported death due to the recent conflict around land issues at the time of the survey.

Selection of towns and households around four concessions

We first create a list of towns affected by concessions (i.e., treatment town) and those not affected by them (i.e., potential control towns) using the comprehensive list of towns around concessions from the Census 2008. In collaboration with the Sustainable Development Initiative (SDI) which works on land rights issues on the ground in most of the concession sites and knowledgeable locals identified by the SDI, we defined towns that are affected by concessions, satisfying either of the following criteria:

- A town is within the boundary of the implemented concession area.
- A town's boundary (where their livelihoods are dependent, e.g., for the collection of non-timber forest products) crosses with agricultural concession boundaries.

After the identification of the affected towns from the comprehensive list of towns in the Census 2008, we identify a pool of potential control towns that meet all of the following criteria:

- A town is outside of any concession boundaries, e.g., agricultural, forestry, or mineral concessions.
- The town's boundary does not cross with any form of concession boundaries.
- There is little spillover effect from towns being affected by concessions, e.g., no major migration or emigration due to concessions.
- The town is within the same clan, district, or county such that similarities in terms of macroeconomic policies hold

Among the treatment pool and potential control towns, we randomly select 24 treatment towns around four concessions. Using the chosen treatment towns, we select control towns from the list of potential control towns with the most similar demographic and socioeconomic characteristics using the Census 2008 data and biophysical factors as detailed in the following section. Table A1 in the Appendix lists demographic, socioeconomic, and biophysical characteristics that are likely to affect both concessions and households' locational decisions and socioeconomic outcome indicators used in our main analysis. We use these variables to construct a propensity score indicating the likelihood of being affected by concessions. We selected 24 control towns with the highest propensity score, having similar biophysical, demographic, and socioeconomic characteristics, with 25 households in each town.

Upon entering the town, a town register is obtained or created with the help of chief or elders in the town. The town register is composed of households that have lived since the beginning of the concession operations. Using the town register, we randomly sample 25 households in each town. Our survey questions include recall questions asking their socioeconomic status "before intervention” before the operation of concessions.

The household survey and biophysical data

In 2018, we collected a total number of 1,288 surveys in 52 towns located across the four counties (Figure 1). Our survey questions include each household’s demographic and socioeconomic information. In particular, our survey includes detailed questions on livelihood indicators (e.g., income, expenditure, and assets) and the use of land and forests that have been identified in the literature to be affected by agricultural concessions. We also ask recall questions on livelihood indicators and land/forest use variables by asking what it was like or the change from before the arrival of concessions. Answers from recall questions have been documented to introduce measurement errors and can create bias in estimations

(Wollburg et al., 2021). We minimize this bias by focusing on recall questions that do not require much precision, such as income and expenditure, and therefore are less prone to recall biases (Bell et al., 2019). The survey questions are documented in the Appendix.

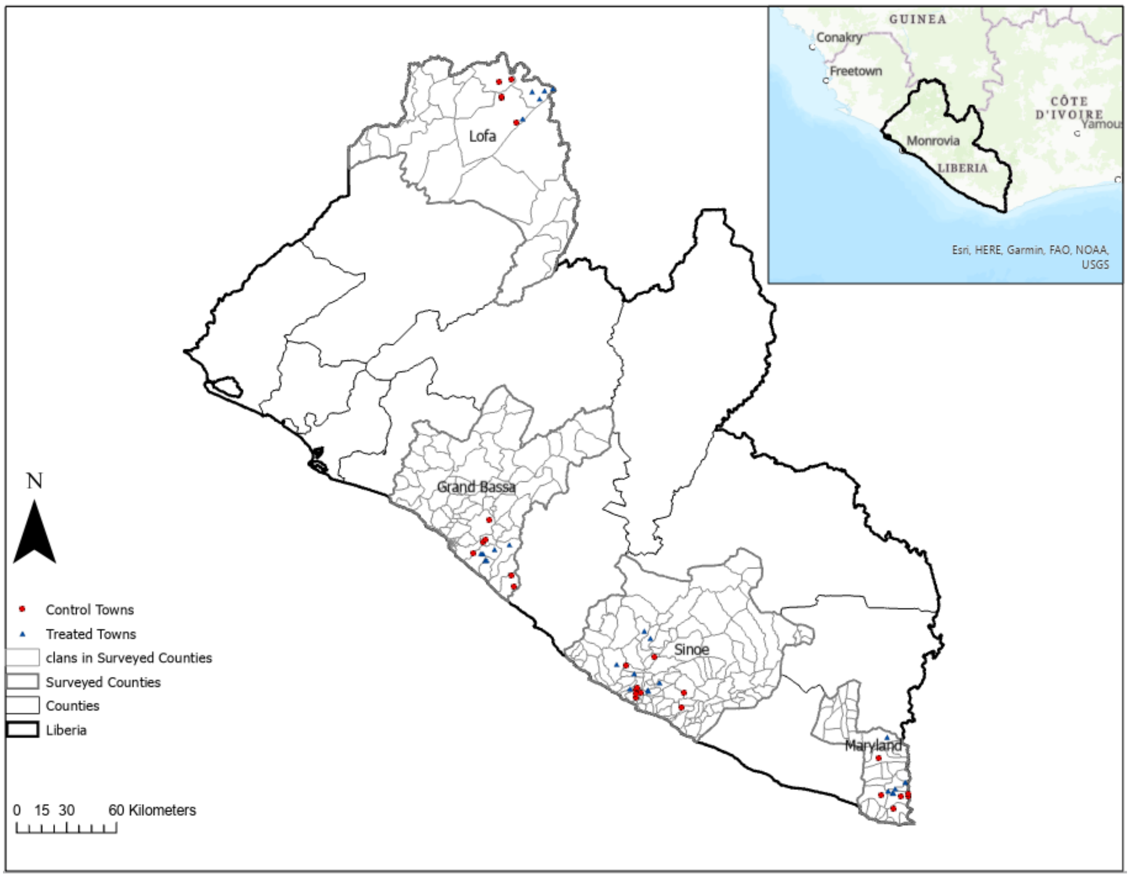

Figure 1. Location of counties and surveyed towns in Liberia

We also control for biophysical characteristics before 2008 by using geographic coordinates of each town extracted from the Census 2008 data. We calculate biophysical variables, including elevation, slope, road density, distance to PA, forest cover 2000, forest loss density between 2001 and 2007, precipitation, night lights, and temperature. We calculate elevation and slope variables using Shuttle Radar Topography Mission 30 m (EROS Center, 2017), road density using roads network data collected by the United Nations Mission in Liberia (UNMIL, 2007), euclidean distance to protected areas using World Database of Protected Areas (Protected Planet, 2018), forest cover and density using global deforestation map

(Hansen et al., 2013), precipitation and temperature using WorldClim data (Fick and Hijmans, 2017), and nighttime lights data by NOAA National Centers for Environmental Information (NCEI, 2018). Descriptive statics of all demographic, socioeconomic, and biophysical variables are in Appendix Table A2.

The balance between control and treatment towns

We test the differences between surveyed treatment and control towns in demographic and socioeconomic information in the 2008 Census and biophysical characteristics in Table 2. We do not find statistically significant differences for all demographic and biophysical variables ($p<0.05$). We also compare differences in livelihood outcome indicators between treatment and control towns using responses from recall questions. While information obtained from recall questions is not a perfect substitute for having baseline survey data before the arrival of concessions, information from recall questions can be used as a proxy for baseline differences in our outcome variables of interest. We find that there are no significant differences in all socioeconomic and labor allocation variables except for the proportion of labor hours spent on agricultural-self-paid and agricultural-wage-paid.

Empirical models

We aim to estimate the causal impacts of agricultural concession operations on various livelihood indicators and understand underlying causal mechanisms. While the lack of significant differences in observable demographic and pre-intervention outcome variables reduces concerns for the differences in treated and control towns biasing the estimated impact, selection into the treatment might be driven by omitted variables. We use difference-in-differences (DID) and instrumental variable estimation methods to address the endogeneity of our treatment of being affected by agricultural concessions and the omitted variable bias.

We take advantage of our recall questions and detailed survey questions on a variety of livelihood indicators to explore impacts on multiple livelihood outcomes and potential causal mechanisms.

Table 2. Differences in demographic, socioeconomic, and biophysical characteristics between affected (treatment) and non-affected towns (control) by agricultural concessions

Variable description	Control	Treatment	Difference
	Mean (S.D.)		(S.E.)
Demographic variables			
Male household head (1/0)	0.67	0.68	0.01
	(0.47)	(0.47)	(0.04)
Household head age(years)	43.69	44.10	0.41
	(11.58)	(13.09)	(1.09)
Household head ethnicity = Bassa (1/0)	0.22	0.22	0.00
	(0.41)	(0.41)	(0.15)
Household head religion = Christianity	0.91	0.82	-0.09
(1/0)	(0.29)	(0.39)	(0.11)
Household head years of formal education	2.53	2.56	0.03
	(1.01)	(0.99)	(0.09)
Total number of household members	6.55	7.01	0.46*
	(2.73)	(3.43)	(0.26)
The number of males 15 years and above	1.60	1.68	0.08
	(1.05)	(1.24)	(0.07)
The number of household members with	2.37	2.48	0.11
above five years of formal education	(1.65)	(2.02)	(0.16)
Biophysical variables			
Forest cover change between 2000 and	2.59	3.66	1.07
2008	(2.04)	(2.37)	(0.93)
Average of average monthly rainfall, 1970-	260.54	254.68	-5.87
2000	(44.89)	(43.74)	(16.86)
Slope	7.91	8.38	0.48
	(1.64)	(2.69)	(0.58)
Distance to the nearest road	1639.69	1846.10	206.41
	(2017.87)	(3451.70)	(1268.34)
Distance to protected areas	29283.42	28945.78	-337.64
	(16384.22)	(19710.93)	(6796.99)
Distance to t	23870.74	24481.43	610.69
	(44883.84)	(48632.62)	(20701.12)
Socioeconomic indicators "before intervention" (using recall questions)			
Household head occupation = Professional	0.03	0.03	0.01
(1/0)	(0.16)	(0.18)	(0.01)
Household head occupation = farmer/crop	0.91	0.83	-0.08*
grower/gardener (1/0)	(0.29)	(0.38)	(0.04)
Household head occupation = Laborer	0.01	0.02	0.01
(1/0)	(0.11)	(0.15)	(0.01)
Income from cash and non-cash sources			
(1/0)	38600.40	45239.88	6639.49

	(41994.36)	(56773.47)	(4556.70)
Total annual expenditure	29893.65	33102.51	3208.86
	(40905.56)	(37228.40)	(3591.44)
Total annual expenditure from all sources	28419.68	32806.26	4386.58
	(29656.65)	(38233.42)	(3419.66)
Asset based wealth score (Calculated from Principal Component Analysis)	(0.05)	0.05	0.10
	(1.80)	(1.78)	(0.12)
Mean average hours per week from above seven years old and working	40.01	39.94	-0.06
	(16.22)	(15.47)	(0.90)
Mean average hours= Agricultural-related	30.85	28.97	-1.88
	(17.42)	(17.19)	(1.38)
Mean average hours= Forestry-related	2.75	3.02	0.27
	(7.51)	(7.03)	(0.46)
Mean average hours= Non-ag and non-forestry	5.88	7.74	1.87
	(11.54)	(13.75)	(1.20)
Proportion average hours per week=Agricultural-related	0.76	0.72	-0.04
	(0.31)	(0.33)	(0.03)
Proportion average hours per week=Forestry-related	0.08	0.08	0.00
	(0.15)	(0.14)	(0.01)
Proportion average hours per week= Non-ag and non-forestry	0.15	0.19	0.04*
	(0.24)	(0.30)	(0.03)
Proportion =Agricultural-self-paid	0.76	0.69	-0.07**
	(0.31)	(0.35)	(0.03)
Proportion =Agricultural-wage-paid	0.01	0.03	0.03***
	(0.06)	(0.15)	(0.01)
Proportion =Forestry-self-paid	0.07	0.07	0.00
	(0.15)	(0.13)	(0.01)
Proportion =Forestry-wage-paid	0.00	0.01	0.00
	(0.04)	(0.06)	(0.00)
Proportion = Non-ag and non-forestry-self-paid	0.11	0.13	0.02
	(0.20)	(0.23)	(0.02)
Proportion =Non-ag and non-forestry-wage-paid	0.04	0.06	0.02
	(0.15)	(0.20)	(0.02)
Observations	658.00	630.00	1288.00

Difference-in-differences estimation

We first estimate the impacts of agricultural concessions on livelihood outcomes by employing the difference-in-differences estimation method using recall data on livelihood outcomes before the arrival of concessions. Information obtained from recall questions can suffer from measurement errors and bias (Wollburg et al., 2021). To mitigate this problem, we use variables that measure access to and use of land and forests that are easier to remember as our major outcome indicators as they require less precision and, therefore, less prone to recall biases (Bell et al., 2019). The use of the recall data enables us to include household fixed effect terms, controlling for household-specific unobservables. However, given the high likelihood of measurement errors and potential bias, we use the instrumental variable approach as our primary estimation method as detailed in the next section.

We estimate the following equation for household *i* in town *j* with household fixed effects:

$$Outcome_{ij} = \alpha + \gamma_i + \beta Post_t + \delta_{impact} Post_t T_j + \boldsymbol{X_{ij}} + \epsilon_{it} \tag{1}$$

where $Outcome_{ij}$ is a variable that indicates households' access to land and forests (for household *i* in town *j*); γ_i is household fixed effects that control for any household-specific unobservables. $Post_t$ indicates a dummy variable indicating whether the time period is before the arrival of concessions (=0) or after the arrival of concessions (=1). $\boldsymbol{X_{ij}}$ is a set of control variables, including households' demographic, socioeconomic, and biophysical information.

Instrumental variable approach

While the DID estimation method purges at least partially the endogeneity problem by controlling for time-invariant unobservables at the household level, there might still be time-variant omitted variables that are correlated with the treatment and the outcome variable. In addition, towns with more households of low socioeconomic status might be more willing to agree with concession operations, i.e., being treated. The estimated impacts can suffer from reverse causality, aggravating the endogeneity bias. We use an instrumental variable approach to mitigate these concerns by exploiting exogenous variations in biophysical characteristics as instruments and estimate the impacts of agricultural concessions on livelihood outcomes using only cross-section data after the arrival of concessions. We run a two-stage least squares regression using biophysical characteristics (slope and deforestation between 2000 and 2008) of surrounding towns outside of clan boundaries and 5 km buffer but within 5-20 km buffer as instruments for the treatment status of a town. We use a 5 km buffer to define surrounding towns that are not part of the same clan but use a 7, 10, 15, 20 km buffer if a town does not have two or more towns within each buffer distance. We use slope and forest cover change, i.e., cumulative deforestation between 2000 and 2008, which affect locational decisions of concessionaires and households as instruments. Conditional on a set of control variables, our identification assumptions are the following:

1) Relevance and independence of potential outcomes/treatments: biophysical characteristics of surrounding towns are highly correlated with the biophysical characteristics of the town of interest and, therefore, the treatment status of the town. Outcome indicators and the treatment status, being affected by concession operations, do not cause changes in the instruments (biophysical characteristics of surrounding towns).
2) Exclusion restriction: surrounding towns' biophysical characteristics do not directly affect the households' livelihood outcomes except through the treatment assignment.
3) Monotonicity: a hypothetical change in the biophysical characteristics of surrounding villages changes the treatment status in the same direction for all units affected by biophysical characteristics.

We test the first relevance assumption by testing the significance of instrument variables in the first stage and show F-statistics on the joint test of how much the instrument adds explanatory power to the regression. The independence of potential outcomes/treatments assumption holds since it is unlikely that livelihood activities and concession operations affect pre-existing biophysical characteristics of surrounding towns. The second exclusion restriction assumption is plausible because livelihood activities such as farming and collection of forest products are defined by and occur within clan boundaries. Therefore, neighboring towns' biophysical characteristics outside of the clan boundary will not directly affect the treatment towns' livelihood outcomes unless through the treatment's assignment. We argue that the monotonicity assumption can generally hold in our case, given that concessions companies for commercial crops are likely to have similar preferences for biophysical characteristics in selecting potential sites for concession operations.

We run the following two-stage least square regression at the household level with the binary treatment status as a dependent variable and biophysical variables as instruments in the first stage:

$$T_j = \alpha + Biophysicals_{-j} + \boldsymbol{X_{ij}} + \epsilon_{ij} \quad (1)$$

where T_{ij} indicates the treatment status of whether a household i is affected by agricultural concessions; $Biophysicals_{-j}$ indicate the averages of slope and forest cover change between 2000 and 2008 of surrounding towns ($-j$) within a buffer (≥ 5 km) from the town j but outside of clan boundaries to which the town j belongs; X_{ij} is a set of households' demographic and socioeconomic variables that are also included in the second stage regression; and ϵ_{ij} is an error term. We use the fitted probability from equation (1) as an instrument for the treatment variable and estimate the following second stage regression:

$$Outcome_{ij} = \alpha + \gamma_c + \beta\widehat{T_i} + Biophysical_j + \boldsymbol{X_{ij}} + \epsilon_{it} \quad (2)$$

where $Outcome_{ij}$ is an array of livelihood indicator variables; γ_c is clan fixed effects that control for any clan-specific changes in resource management, given that many livelihood activities are defined by the clan. We use income, expenditure, asset-based wealth index, and food security as indicators of the general welfare. Other outcome variables include agricultural and forestry-related activities such as the amount of agricultural production and harvest of forest products and labor allocations. We focus on variables that indicate changes from before the intervention

Our use of surrounding towns' biophysical characteristics as instruments is similar to papers that have used average or proportional values of the neighboring farmers' characteristics to address the endogeneity issues (Birthal et al., 2015; Li et al., 2021; Tesfaye and Tirivayi, 2020). In Uganda, Tesfaye and Tirivayi (2020) study relationships between crop diversification, household welfare, and consumption smoothing in the presence of climate changes by employing instrumental variables to account for unobserved heterogeneity and potential reverse causality. They use mean temperature and elevation, rainfall shock, and average village-level crop diversification as the instruments. The choice of average village-level crop diversification is premised on the fact that social networks and neighborhood effects influence agricultural technology and production decisions. Similarly, Birthal et al. (2015) investigate the impacts of crop diversification into high-value crops (HVCs) on farmers' livelihood outcomes in India. The authors use HVCs' growing farmers' proportion in the observed farmer's network (excluding the farmer) as an instrument. It is more likely that a farmer will adopt HVCs if many neighboring farmers cultivate HVCs, and the cultivation of HVCs by neighboring farmers will not directly affect the outcome. The network of a farmer includes other farmers whose mean characteristics can affect that of the farmer. These factors include education, age, geographical proximity, and status. Li et al. (2021) also use the instrumental variable approach while studying the relationship between profit variability and crop diversity in south China. In a search for an appropriate instrumental variable, the authors exploit the average crop diversity of farmers in the same village exclusive of the observed farmer. They justified the approach stating that farmers in the same neighborhood can plant similar crops while their profits do not directly affect others.

Results

A decrease in access to land and forests and food security

We find evidence supporting limited access to agricultural and forest lands as a result of concession operations. Table 3 presents the difference in the amount of agricultural and forest lands between control and treatment towns after concession operations compared to the difference before concession operations using DID with fixed effects. The amount of both owned and the cultivated area has decreased for households in treatment towns by 9% and 12%, respectively (columns 1 - 2), compared to those in control towns. The amount of community forest area households have access to has also decreased by a more significant amount of 21% in the treatment towns compared to control towns (column 3). We find a similar pattern of decreasing access to cultivation and forest lands when using IV regressions (columns 4 - 6 in Table 3). Households in treatment towns are 21-25% more likely to indicate that the cultivation amount of communally or owned land area has decreased after concession operations (columns 4 - 5 in Table 3).

Table 3. Estimation results showing the difference in land and forest areas between control and treatment towns from before to after the concession operations

	Ln (Owned land area)	Ln (Cultivation area)	Ln (Total community forest area household has access to)	The type of cultivated land area has decreased (Yes = 1)	
				Community-owned	Family-owned or own
	(1)	(2)	(3)	(4)	(5)
Post = 1	0.024***	0.015**	-0.035**		
	(0.0087)	(0.0063)	(0.035)		
Treatment				0.21***	0.25***
				(0.056)	(0.039)
Treatment × Post	-0.092***	-0.121***	-0.21***		
	(0.030)	(0.019)	(0.039)		
Fixed effects	Household	Household	Household	Clan	Clan
First-stage F-statistics				26.8	26.8
R^2	0.020	0.042	0.292		
Observations	2530	2530	1949	1252	1252

Note. Regressions in columns (1) - (5) include the following additional controls (coefficients not reported): binary variables equal to one if a household owns a hoe, tractor, wheelbarrow; a binary variable equal to one if a household has a savings account; a binary variable equal to one if a household has any loan; total number of work hours/week of household members who are over 7 years old. Regressions in columns (4) -(5) include additional controls: household head's age, years of formal education; the total number of household members; the number of males 15 years and above; the number of household members with above five years of formal education; binary variables equal to one if a male household head, household head's ethnicity is Bassa, household head is a Christian, household head's primary occupation is professional, farmer/crop grower/gardener, or laborer. Standard errors are clustered at the clan level and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As a result of the decrease in access to lands and forests, we find evidence suggesting that the amount of agricultural production for subsistence has decreased significantly. The number of subsistence crops that households decreased (increased) production amount is higher (lower) by 0.8 (0.96) in treatment towns than that in control towns. We also find a similar pattern regarding access to forests, which provides resources for local livelihoods. While there is no significant difference in the number of forest products that they harvest between treatment and control towns (column 4 in Table 4), we find that households in the treatment towns experienced a decrease in the number of forest products that they harvest, potentially resulting from limited access to forests. Households in the treatment towns have significantly more forest products that decreased the harvest amount by 0.53 than those in control towns (column 5). The decrease in the subsistence agricultural production and the amount of forest product harvests indicate that households in the treatment towns are more likely to face greater food insecurity.

Table 4. Estimation results showing differences in the number of subsistence crops and the number of forest products between treatment and control towns

	The number of crops with changes in subsistence ag production amount among five major crops: cassava, bitterballs, rice, pepper, and plantain			The # of forest products	
	Decrease	Same	Increase	Harvested total	Decreased harvesting
	(1)	(2)	(3)	(4)	(5)
Treatment	0.81**	0.35	-0.96***	0.20	0.53***
	(0.40)	(0.29)	(0.23)	(1.40)	(0.18)
Fixed effects	Clan	Clan	Clan	Clan	Clan
First-stage F-statistics	30.3	30.3	30.3	30.3	30.3
Observations	1239	1239	1239	1239	1239

Note. Regressions in columns (1) - (5) include the following additional controls (coefficients not reported): household head's age and years of formal education; the total number of household members; the number of males 15 years and above; the number of household members with above five years of formal education; binary variables equal to one if a male household head, household head's ethnicity is Bassa, household head is a Christian, household head's primary occupation is professional, farmer/crop grower/gardener, or laborer; distance (km) to the nearest market and district capital; the total amount of land (ha) that a household owns and the total amount of land (ha) that a household cultivates (owned, rented or communal); number of small livestock (Chicken, duck, guinea fowl, etc.). Standard errors are clustered at the clan level and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Indeed, our investigation of the level of perceived food security seems to correspond to the expected greater food insecurity in treatment towns. Households in the treatment towns are 80% more likely to respond that any member of their household was unable to eat healthy and nutritious food because of a lack of money, harvest or other resources compared to those in control towns. The same households in the treatment towns are 37% more likely to have skipped a meal compared to those in control towns. These results are consistent with the results in Tables 3 and 4 showing the decrease in the amount of land and forests that households have access to and the decrease in the amount of subsistence agricultural production and forest products.

Table 5. Estimated differences in perceived food security between treatment and control towns

	In the last year, was there a time when any member of your household _________because of a lack of money, harvest or other resources? (Yes=1, No=0)			
	went w/o eating for a whole day	had to skip a meal	was unable to eat healthy/ nutritious	was worried
	(1)	(2)	(3)	(4)
Treatment	0.59* (0.32)	0.37** (0.17)	0.80*** (0.25)	0.54** (0.28)
Fixed effects	Clan	Clan	Clan	Clan
First-stage F-statistics	29.8	30.3	30.5	30.3
Observations	1238	1237	1237	1237

Note. Regressions in columns (1) - (4) include the following additional controls (coefficients not reported): household head's age and years of formal education; the total number of household members; the number of males 15 years and above; the number of household members with above five years of formal education; binary variables equal to one if a male household head, household head's ethnicity is Bassa, household head is a Christian, household head's primary occupation is professional, farmer/crop grower/gardener, or laborer; distance (km) to the nearest market and district capital; the total amount of land (ha) that a household owns and the total amount of land (ha) that a household cultivates (owned, rented or communal); number of small livestock (Chicken, duck, guinea fowl, etc.). Standard errors are clustered at the clan level and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Coping mechanisms: changes in income sources and labor allocations

While we find a significant decrease in access to land and forests, resulting in a decrease in food security, we do not find significant differences in general welfare indicators such as aggregated annual income and expenditure between control and treatment towns (see Table A3 in the appendix). However, we find that the asset-based wealth index is lower by 0.65 (p<0.10) in treatment towns than in control towns, which might reflect longer-term negative impacts of concession operations.

Our investigation of differences in labor allocations and migration between control and treatment towns indicates a significant difference in the amount and proportion of labor allocations to agricultural production activities. Households in treatment towns worked 4.9 hours less in the agricultural sector (Table 6), which is equivalent to 12% fewer total working hours (Table A4 in the Appendix). This is consistent with the above results showing a decrease in the amount of cultivation area that can cause a reduction in the labor demand for agricultural production. Further investigation of the type of agricultural activities (self-employed vs. wage labor) in Table A4 in the Appendix reveals that the decrease is associated with a reduction in self-employed households in the agricultural sector among households in treatment towns.

Our investigation of the differences in the number of migrants supports the hypothesis of an increased migration as a result of agricultural concession operations. We find that the number of migrants since the arrival of concessions in treatment towns is 0.63 more than those in control towns (Table 6). The increase in the number of migrants is more prevalent for households who do not depend on forestry but on other sectors, including agricultural production and other off-farm income opportunities (column 6 in Table 6).

Table 6. Estimated differences in the average weekly number of hours spent in agricultural, forestry-related, and non-ag/forestry activities and in the total number of migrants after concession operations

	Average weekly # of hours spent in			Total number of migrants since the arrival of concessions		
	Agriculture	Forestry -related	Non-ag/forestry	All households	Households dependent on forestry	Households dependent on non-forestry
	(1)	(2)	(3)	(4)	(5)	(6)
1=treatment and 0=control	-4.85^{**} (2.17)	2.08 (2.62)	-1.44 (1.43)	0.63^{***} (0.15)	0.61 (0.42)	0.79^{***} (0.24)
Fixed effects	Clan	Clan	Clan	Clan	Clan	Clan
First-stage F-statistics	28.88	28.88	28.88	26.46	21.80	17.10
Observations	1142	1142	1142	1254	431	823

Note. Regressions in columns (1) - (6) include the following additional controls (coefficients not reported): household head's age and years of formal education; the total number of household members; the number of males 15 years and above; the number of household members with above five years of formal education; binary variables equal to one if a male household head, household head's ethnicity is Bassa, household head is a Christian, household head's primary occupation is professional, farmer/crop grower/gardener, or laborer; distance (km) to the nearest market and district capital; the total amount of land (ha) that a household owns and the total amount of land (ha) that a household cultivates (owned, rented or communal); number of small livestock (Chicken, duck, guinea fowl, etc.). Standard errors are clustered at the clan level and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As a result, we find some significant differences in income sources between households in the treatment and control towns. There seem to be an increase in income from land/house rent and remittances and a decrease in income from off-farm jobs. More specifically, we find that households in treatment towns are 6.8% more likely to have land/house rent as an income source than those in control towns. These might reflect households receiving payments from concession companies for using their lands, which can be a short-term benefit of having concessions around their towns. On the other hand, there has been a shift in the type of labor income that households make. Treatment towns are 37% and 8.6% less likely to have off-farm wage labor/casual earnings and off-farm salaried income, respectively, and 14% more likely to have remittances as income sources than control towns. On-farm wage labor/casual earnings do not significantly differ between treatment and control towns. This might indicate that there has been some on-farm employment from concession operations in treatment towns from nearby concession operations. Still, it is not significant enough to increase the income of households in treatment towns. Whether we use the natural log of income or the proportion of income over the total annual income as the dependent variable, these trends remain consistent.

Table 7. Estimated differences in income categories between control and treatment towns

	Had any income from each category (Yes = 1, No=0)					
	Rent (land/house)	On-farm wage labor/casual earnings	Off-farm wage labor/casual earnings	Off-farm salary	Remittance	Selling non-timber forest products
	(1)	(2)	(3)	(4)	(5)	(6)
1=treatment and 0=control	0.068^{***} (0.026)	-0.105 (0.168)	-0.37^{***} (0.077)	-0.086^{**} (0.033)	0.14^{***} (0.051)	-0.124 (0.076)
Fixed effects	Clan	Clan	Clan	Clan	Clan	Clan
First-stage F-statistics	26.7	26.7	26.7	26.7	26.7	26.7
Observations	1272	1272	1272	1272	1272	1272

Note. Regressions in columns (1) - (6) include the following additional controls (coefficients not reported): household head's age and years of formal education; the total number of household members; the number of males 15 years and above; the number of household members with above five years of formal education; binary variables equal to one if a male household head, household head's ethnicity is Bassa, household head is a Christian, household head's primary occupation is professional, farmer/crop grower/gardener, or laborer. Standard errors are clustered at the clan level and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Discussion and conclusion

Many African governments, after the 2007-2008 global recession, contracted their vast arable land to investors with the hope of revamping the agriculture sector, i.e., changing from subsistence to a viable commercial level, creating employment opportunities, developing the rural areas, and providing social amenities (Bunte et al., 2018). Commercial large-scale land concessions and investments have been widespread, with over 80% of these in the agricultural sector (Osabuohien et al., 2019; Shete and Rutten, 2015. While the evidence on the impacts of these large-scale land concessions is mixed, much of the literature has found extensive evidence of the adverse effects of concessions on households' livelihoods. Some of the findings in the literature include decreased access to land (especially small landholders), leading to worsening land conflicts and food security and increased deforestation, resulting in a reduction in the provision of ecosystem services (e.g., good water quality, forest products, carbon sequestration) (Jung, 2018). Our analysis of the impacts of agricultural concessions in Liberia shows that concession operations have decreased access to crop land (9-12%) and community forests (21%), which worsened food insecurity by causing a decrease in agricultural production for subsistence and the number of harvested forest products. While these results are consistent with others finding negative impacts of large-scale land concessions, our analysis provides further evidence on how households affected by concessions adapt to and cope with the decrease in access to land and forests through changes in labor allocations.

Our results suggest that the decrease in access to land and forests caused a reduction in the amount of agricultural production and the number of forest products that households harvest for subsistence, undermining food security. Our estimates suggest that the number of major subsistence crops and forest products decreased by 0.8 and 0.5, respectively. These decreases are not insignificant given that it is among five major subsistence crops (cassava, bitter balls, rice, pepper, and plantain) and that the average number of non-timber forest products that households harvest is 2.9 across all households. The decrease in the number of subsistence crops and forest products harvested seems to have led to households' perception of food insecurity. An estimated 80% more households in the treatment towns responded that any member of their household was unable to eat healthy and nutritious food because of a lack of money, harvest, or other resources compared to those in control towns.

Our comparison of households' labor allocations and the source of income between control and treatment towns suggests that households in the treatment town worked 4.9 hours less in the agricultural sector than those in the control towns, driven by the decrease of self-employed agricultural activities. This is consistent with our theoretical model suggesting a reduction in employment for agricultural production, presumably because of the reduction in access to agricultural lands (Hypothesis 1). On the other hand, we do not observe significant differences in the proportion of time spent on wage or casual labor for agricultural production between control and treatment towns (Table A4). We interpret this as suggestive evidence that agricultural concessions might have provided some casual employment opportunities, which might not have been enough to offset the decrease in the total employment in agricultural production (Hypothesis 2). Lastly, we find supporting evidence that concession operations have increased the number of migrants by 0.63 (Hypothesis 3), which is significant given the average number of migrants before and after concession operations is 0.24 and 0.40, respectively.

Further investigation of income categories shows consistent results with the above findings. It provides a further narrative on how households have been coping with the shock given by the arrival of concession operations. Income from land/house rent and remittances from migrants seem to have offset the lost income from the decrease in agricultural activities. Households in treatment towns are 6.8% and 14% more likely to have land/house rent and remittances as their income sources than those in control towns, respectively. We suspect that the decrease in off-farm income of households in treatment towns might have been primarily driven by the increase in migration of labor forces.

Consistent results from theoretical and empirical models on labor allocations, which have not been explored frequently with quantitative data, contribute to the literature on the impacts of large-scale land concessions and environmental/development economics literature. Methodologically, our collection of unique data with relevant indicators and a sampling method to overcome endogeneity issues arising from the use of observational data helps us causally estimate the changes in access to resources and livelihoods in affected towns by agricultural concessions. However, we caveat that our findings hinge on identification assumptions detailed in the *Instrumental variable approach* section. With a decrease in access to agricultural lands and forests and limited employment opportunities, our results highlight how households mitigate economic shocks by increasing the number of migrants and supplementing income from remittances. These findings have broader implications for many developing countries that implement large-scale land concessions for agricultural production.

Along with protocols to secure private and communal rights to agricultural and forest lands, the policy that governs large-scale land concession should ensure contracts for these concessions include well-defined and clearly-stated benefits to the investors and communities. The investors may be held accountable for any adverse outcome contrary to the terms and conditions explicitly stated in their contract. Additional research is needed to estimate the long-term impacts of agricultural concessions as our results reveal evidence of decreased asset-based wealth index in the treatment towns at a 10% level of significance.

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Appendix

Construction of welfare index using principal component analysis

Our constructed welfare index aims to assess the long-term socioeconomic position of the observed households. We create the welfare index using the durable assets owned by the different households in our survey sample, including their utilities, housing infrastructures, and characteristics. Asset-based scores or indexes can be used as an alternative to other forms of wellbeing or poverty measurement(Sahn and Stifel, 2003). Compared with elicited income or expenditure data, an asset-based wealth index suffers less measuring and reporting errors (Kolenikov and Angeles, 2009, 2004) because the survey takers can observe and record asset ownership. In addition, the use of income or consumption expenditure requires extensive resources(Vyas and Kumaranayake, 2006). In the survey, respondents were asked questions about their income in cash and non-cash before and after the concession. However, establishing that the provided income is accurate is difficult because many respondents may be unfamiliar with accounting principles and engage in seasonal jobs (Vyas and Kumaranayake, 2006).

Following Filmer and Pritchett (2001), we construct the socioeconomic index using the available data on household assets, utilities, and dwelling qualities using principal component analysis(PCA). Many researchers have adopted the PCA method of constructing welfare index in performing analyses of socioeconomic inequalities, especially within the Demographic and Health Survey (DHS)(Filmer and Scott, 2012; Varghese et al., 2021; Yeh et al., 2020). We, however, use the categorical variables with ordinal information as an ordinal variable rather than dummy indicators for any variable with more than two categories in their method. One advantage of using the ordinal variable is the preservation of the ordinal information. It also prevents spurious correlations(Kolenikov and Angeles, 2004). The household assets used in constructing the welfare index include radio, phone, mosquito net, television, fridge, stove, house, possession of a savings account, livestock. The dwelling utilities and qualities like water, fueling, and light source are inputted as ordinal variables, while the remaining variables are dummy variables. After that, we compare our proposed welfare index with educational attainment to validate our strategy(Lovaton Davila et al., 2021).

Table A1. Descriptive statistics

Variable description	Before "intervention"	Current survey period 2017	Difference
	Mean (S.D.)		(S.E.)
Demographic variables			
Male household head (1/0)	0.673	0.673	-0.000
	(0.469)	(0.469)	(0.000)
Household head age(years)	43.889	43.889	0.000
	(12.343)	(12.343)	()
Household head ethnicity = Bassa (1/0)	0.219	0.219	0.000
	(0.414)	(0.414)	()
Household head religion = Christianity (1/0)	0.865	0.865	0.000
	(0.342)	(0.342)	(0.000)

Household head years of formal education	2.544	2.544	-0.000
	(0.998)	(0.998)	()
Total number of household members		6.772	0.000
	()	(3.099)	(0.000)
The number of males 15 years and above		1.639	0.000
	()	(1.146)	(0.000)
The number of household members with above five years of formal education		2.426	0.000
	()	(1.840)	(0.000)
Household head occupation = Professional (1/0)	0.029	0.029	-0.000
	(0.167)	(0.167)	()
Household head occupation = farmer/crop grower/gardener (1/0)	0.866	0.866	0.000
	(0.340)	(0.340)	(0.000)
Household head occupation = Laborer (1/0)	0.017	0.017	0.000
	(0.130)	(0.130)	()
Assets			
Total amount of land (ha) a household owns	96.794	182.987	86.194
	(2,375.236)	(4,507.097)	(88.351)
Total amount of land (ha) a household cultivates (owned, rented or communal)	4.164	3.298	-0.866**
	(23.508)	(16.944)	(0.419)
Hoe (1/0)	0.568	0.589	0.021**
	(0.496)	(0.492)	(0.010)
Tractor (1/0)	0.010	0.011	0.001
	(0.100)	(0.104)	(0.003)
Wheelbarrow (1/0)	0.108	0.136	0.028***
	(0.311)	(0.343)	(0.006)
A member of the household has a savings account (1/0)	0.104	0.117	0.013***
	(0.305)	(0.322)	(0.005)
A member of the household has any loan (1/0)	0.018	0.025	0.007*
	(0.133)	(0.156)	(0.004)
number of small livestock (Chicken, duck, guinea fowl...)	9.556	7.662	-1.894***
	(9.955)	(8.413)	(0.284)
Proximity variables			
Distance (km) to the nearest market		8.684	0.000
	()	(11.388)	(0.000)
Distance (km) to the nearest district capital		11.788	0.000
	()	(15.086)	(0.000)
Wealth variables			
Aggregated Income	41,847.969	54,467.020	12,619.049***
	(49,865.668)	(65,830.023)	(1,614.499)
Expenditures	31,463.148	43,702.016	12,238.868***
	(39,167.891)	(52,987.453)	(1,495.980)
Wealth Index	0.002	-0.000	-0.002
	(1.788)	(1.757)	(0.032)
Biophysical variables (instrumental variables)			
Mean slope	8.546	8.546	-0.000
	(2.046)	(2.046)	(0.000)
Mean forest change	3.078	3.078	0.000

	(1.471)	(1.471)	(0.000)
Socioeconomic Indicators			
Mean average hours per week from above seven years old and working	39.976	40.562	0.586***
	(15.851)	(15.787)	(0.168)
Mean average hours= Agricultural-related	29.933	30.601	0.668***
	(17.325)	(17.376)	(0.232)
Mean average hours= Forestry-related	2.880	3.189	0.308
	(7.278)	(6.668)	(0.240)
Mean average hours= Non-ag and non-forestry	6.786	6.392	-0.395*
	(12.693)	(12.244)	(0.230)
Proportion average hours per week=Agricultural-related	0.741	0.744	0.003
	(0.322)	(0.317)	(0.004)
Proportion average hours per week=Forestry-related	0.079	0.083	0.005
	(0.148)	(0.140)	(0.004)
Proportion average hours per week= Non-ag and non-forestry	0.167	0.159	-0.008
	(0.271)	(0.265)	(0.005)
Proportion =Agricultural-self-paid	0.724	0.714	-0.009
	(0.334)	(0.338)	(0.006)
Proportion =Agricultural-wage-paid	0.019	0.029	0.010***
	(0.112)	(0.140)	(0.003)
Proportion =Forestry-self-paid	0.074	0.076	0.002
	(0.140)	(0.130)	(0.004)
Proportion =Forestry-wage-paid	0.005	0.007	0.002
	(0.054)	(0.057)	(0.001)
Proportion = Non-ag and non-forestry-self-paid	0.115	0.104	-0.011***
	(0.217)	(0.203)	(0.004)
Proportion =Non-ag and non-forestry-wage-paid	0.052	0.056	0.003
	(0.175)	(0.179)	(0.002)
Observations	1,288	1,288	2,576

Table A2. Demographic and socioeconomic characteristics from Census 2008 and biophysical variables that are used to match similar control and treatment towns

Variable description	Control	Treatment	Difference
	Mean (S.D.)		(S.E.)
Demographic variables			
Household head male (%)	0.698	0.761	0.063
	(0.458)	(0.424)	(0.041)
Household head age (years)	44.071	43.872	-0.200
	(15.477)	(15.583)	(0.869)
Religion = traditional (%)	0.013	0.008	-0.005
	(0.172)	(0.122)	(0.004)
Household Labor Force over 14 (%)	0.615	0.596	-0.019
	(0.238)	(0.247)	(0.019)
Etnicity = Egre (%)	0.250	0.112	-0.138
	(0.428)	(0.311)	(0.111)
Years at residence	15.053	18.640	3.587
	(13.750)	(13.276)	(4.056)
Household Head Education Years	3.823	2.725	-1.098**
	(4.568)	(4.221)	(0.441)
Unemployment (%)	0.075	0.122	0.048
	(0.341)	(0.564)	(0.049)
Occupation = service (%)	0.105	0.101	-0.004
	(0.279)	(0.258)	(0.051)
Occupation = skilled agriculture/fishery (%)	0.594	0.724	0.129
	0.685	0.851	0.166*
	(0.427)	(0.306)	(0.081)
PCA			
pca1	-0.540	-0.785	-0.245
	(0.662)	(0.602)	(0.227)
pca2	0.168	0.161	-0.007
	(0.232)	(0.333)	(0.124)
pca3	-0.116	-0.122	-0.007
	(0.504)	(0.741)	(0.292)
Work status			
Unpaid family worker (%)	0.346	0.284	-0.062
	(0.395)	(0.389)	(0.077)
Household Member_ Rubber Farming (%)	0.112	0.081	-0.031
	(0.314)	(0.273)	(0.044)
Household Member_ Oil Palm (%)	0.054	0.152	0.098
	(0.226)	(0.359)	(0.068)
Utilities/Infrastructures			
Drinking Water: River, Lake, or Stream (%)	0.357	0.515	0.157
	(0.479)	(0.498)	(0.141)
Palm Oil Lamp (%)	0.618	0.763	0.144**
	(0.484)	(0.424)	(0.067)
Cooking Fuel_ Kerosene (%)	0.011	0.014	0.004
	(0.103)	(0.118)	(0.009)

Distance to Health Facility (1=on premise to 5=5miles and above)	3.426 (1.675)	4.293 (1.308)	0.867** (0.403)
Distance to School (1=on premise to 5=5miles and above)	2.023 (1.310)	1.802 (1.420)	-0.222 (0.308)
Distance to Water Source (1=on premise to 5=5miles and above)	1.245 (0.760)	1.204 (0.618)	-0.042 (0.107)
Biophysical variables			
Forest cover change between 2001 and 2007	3.323 (2.575)	3.507 (2.351)	0.184 (1.224)
Average of average monthly rainfall, 1970-2000	250.952 (44.382)	257.013 (40.521)	6.061 (17.179)
Slope	8.342 (1.826)	8.792 (3.023)	0.450 (0.748)
Distance to the nearest road	1,070.378 (1,763.980)	2,268.555 (3,905.992)	1,198.177 (1,522.355)
Distance to protected areas	28,788.941 (17,095.527)	26,744.246 (20,189.701)	-2,044.695 (7,778.570)
Distance to t	38,676.441 (53,484.496)	31,767.455 (53,458.785)	-6,908.985 (27,480.814)
Forest Cover 2000	60.719 (7.246)	61.451 (8.567)	0.732 (2.754)
Min_t_dist_fix	7,593.090 (6,711.065)	3,181.714 (6,084.356)	-4,411.376* (2,158.872)
Observations	1,315	1,687	3,409

Table A3. IV for aggregate income, expenditure, and wealth index

	Income	Expenditure	Wealth Index
	(1)	(2)	(3)
Treatment	1624.8	-400.3	-0.65*
	(14277.3)	(11313.1)	(0.37)
Fixed effects	Clan	Clan	Clan
First-stage F-statistics	26.5	26.4	25.5
R^2	0.199	0.160	0.397
Observations	1254	1253	1225

Note. Regressions in columns (1) - (3) include the following additional controls (coefficients not reported): household head's age and years of formal education; the total number of household members; the number of males 15 years and above; the number of household members with above five years of formal education; binary variables equal to one if a male household head, household head's ethnicity is Bassa, household head is a Christian, household head's primary occupation is professional, farmer/crop grower/gardener, or laborer. Standard errors are clustered at the clan level and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4. IV For individual category (self-employed and paid)

	Proportion of weekly # of hours spent in								
	Agriculture			Forestry-related			Non-ag and non-forestry		
	Total	Self employed	Wage/ salary	Total	Self employed	Wage/ salary	Total	Self employed	Wage/ salary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1=treatment and 0=control	-0.12^{***} (0.034)	-0.11^{**} (0.048)	-0.011 (0.026)	0.052 (0.042)	0.038 (0.035)	0.013 (0.013)	-0.019 (0.039)	0.013 (0.054)	-0.032 (0.028)
Observations	1142	1142	1142	1142	1142	1142	1142	1142	1142

Note. Regressions in columns (1) - (9) include the following additional controls (coefficients not reported): household head's age and years of formal education; the total number of household members; the number of males 15 years and above; the number of household members with above five years of formal education; binary variables equal to one if a male household head, household head's ethnicity is Bassa, household head is a Christian, household head's primary occupation is professional, farmer/crop grower/gardener, or laborer; distance (km) to the nearest market and district capital; the total amount of land (ha) that a household owns and the total amount of land (ha) that a household cultivates (owned, rented or communal); number of small livestock (Chicken, duck, guinea fowl, etc.). Standard errors are clustered at the clan level and reported in parenthesis. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.