Online Appendix

Cash Crops and the Development-Environment Tradeoff: Evidence from Benin

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A1 Validating the Quality of Gridded GDP

We use high-resolution (25°) gridded GDP data from Rossi-Hansberg and Zhang (2025) (RHZ) as our measure of local incomes. This appendix discusses the quality of RHZ data and validates it against survey-based household wealth measures from DHS.

RHZ performs well in rural areas A concern with using gridded data on economic activity, such as nightlights (NTL), is that these data products perform poorly in rural areas (Gibson et al., 2020). For example, NTL has two key weaknesses: (i) "saturation" in urban areas, where sensors max out in bright regions, and (ii) limited variation in rural areas, where lights are too dim to capture economic activity.

RHZ addresses both issues by combining NTL with additional predictors: (1) land use and crop output to capture agricultural income, (2) population density to reflect settlement size, and (3) sectoral emissions to capture production activity. This richer set of inputs allows the model to distinguish between rural areas that look equally "dark" in NTL but differ sharply in economic activity, thereby reducing the rural noise problem.

To formally show the strong model performance of RHZ, especially in rural areas, we summarize findings from the data document of Rossi-Hansberg and Zhang (2025). Table 1 of RHZ shows that in the 0.25°product, NTL explains a small portion of GDP variance (4 units), while population, urban extent, and emissions contribute equally important explanatory power. Figure 2 of RHZ further shows that GDP values widely across low-population (rural) areas, highlighting the influence of other factors that determine GDP. By adding these "other factors" to the prediction model, RHZ improves prediction accuracy in rural settings compared to using NTL alone.

Validating RHZ estimates The accuracy of RHZ estimates can be assessed in places with subnational GDP data. Indeed, RHZ train a random forest model on a wide set of countries where detailed subnational GDP is available from national statistical agencies. Out-of-sample performance yields an R^2 above 0.92 for GDP levels and 0.62 for annual changes, demonstrating that the model generalizes beyond the training set.

To validate GDP estimates for Benin, we conduct our own cross-sectional validation by matching DHS survey clusters to the nearest GDP grid cell and regressing log GDP on the household wealth index. Results in Table A1 below show a positive correlation in both urban and rural areas. The correlation is stronger in rural areas, addressing the concern that RHZ may not pick up household wealth in rural areas.

Table A1: Correlation between DHS wealth index and GDP

	Urban	Rural
	(1)	(2)
	Log GDP	Log GDP
Wealth Index (scale 1-5)	0.002	0.011**
	(0.003)	(0.005)
Household Controls	Yes	Yes
Geography Controls	Yes	Yes
Department FEs	✓	✓
Observations	1073	1793
R^2	0.701	0.296

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are a household cross section. Columns 1 and 2 are the subset of urban and rural DHS households, respectively. Wealth index is the household wealth index from DHS on a scale of 1-5. The outcome is Log GDP per capita in the RHZ grid cell encompassing the corresponding DHS cluster. Regressions include survey weights and controls for household size, language, rain, temperature, lat/lon, and nightlights. Standard errors are heteroskedasticity-robust.

A2 Hansen et al. (2013) versus VCF Forest Cover

This appendix section provides a discussion on the relative merits of Hansen et al. (2013) versus VCF (Townshend et al., 2017) for measuring forest cover change in our context. The Hansen et al. (2013) data product defines "loss" as a one-time stand-replacement event relative to 2000, making it asymmetric: pixels are flagged when cleared but never revert if trees regrow or are re-planted. By contrast, VCF is continuous and symmetric, recording percent changes in canopy cover that captures both forest loss and gain.

Analysis with Hansen Hansen data might seem preferable for our analysis because it records only forest loss. However, when we replicate our main OLS and IV specifications (Equations 1 and 6 in main text) with Hansen's deforested share of arrondissement land area as the outcome, coefficients are near-zero and statistically insignificant (Table A2, Columns 1 and 2). We discuss two explanations for zero forest change with Hansen data.

Table A2: Robustness: Hansen (2013) Data

	Deforestation Share (Unmasked)		Deforestation Share (Masked)	
	(1) OLS	(2) IV	(3) OLS	(4) IV
CashewShare	-0.002 (0.001)	0.007 (0.006)	-0.001 (0.001)	0.005 (0.005)
Agrochemicals	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Arrondissement FEs	✓	✓	✓	✓
Department × Year FEs	✓	✓	✓	✓
KP (2006) F-Stat		19.84		19.84
Observations	412	412	412	412

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. The outcome in columns 1 and 2 is share of arrondissement land area deforested relative to 2000 from Hansen et al. (2013). The outcome in columns 3 and 4 is the same, but excludes cashew cells in 2015. "CashewShare" is land share under cashews. Columns 1 and 2 are estimated via OLS. Columns 2 and 4 are instrumented with global cashew price variance interacted with baseline cashew share. All specifications include controls for agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

- First, Hansen may classify tree crops as "forest" so that when natural forest is cleared and replanted with cashews, no net change is recorded. To explore this, we masked baseline cashew pixels from Hansen maps so that only forest loss *outside* baseline cashew plots is measured. Yet the results remain zero (Table A2, Columns 3 and 4). Note that such misclassification should only occur if new cashew trees exceed

Hansen's 5m height threshold, which is unlikely for newly transplanted saplings. This raises the question of why we do not detect forest loss with Hansen data.

- A second, more likely, explanation for zero forest change with Hansen data is that cashew cultivation in Benin is often patchy and intercropped with other native trees (Chabi Sika et al., 2013). Hansen explicitly excludes partial forest clearing from its definition of deforestation, noting in the data documentation that "Forest degradation, for example selective removals from within forested stands that do not lead to a non-forest state, was not included in the change characterization" (Hansen et al., 2013) (page 7). Therefore, if cashew orchards retain taller native trees, the algorithm will not flag those pixels as "loss".

VCF Advantage An advantage of VCF over Hansen is that VCF measures percent forest cover, which is a continuous metric that can capture partial forest loss. A disadvantage is that it is symmetric (records both loss and gain), meaning that cashew trees replacing forest could appear as "gain". Reassuringly, as we show in Stylized Fact I (Section 4.1, Figure 4), VCF does not classify cashew trees as forest, reducing misclassification risk and making VCF a more suitable choice for capturing forest displacement in our context.

A3 Price Volatility and Production: Sandmo (1971) vs. Barrett (1996)

Identification via our shift-share instrument relies on the interaction of global price volatility with baseline cashew land share to generate a source of exogenous variation land allocated to cashew production (Section 5). This appendix elaborates the economic logic and empirical evidence linking price volatility to land cultivation decisions.

Land allocation decisions under crop price uncertainty depend on farmers' risk preferences and available risk coping strategies. Classical economic theory predicts that price volatility discourages cultivation of risky crops. Sandmo (1971) provides the canonical theory that risk-averse producers facing higher price variance reduce output, particularly at the extensive margin. This theory is supported by substantial empirical evidence from Sub-Saharan Africa and elsewhere (Krah, 2023; Lundberg and Abman, 2022; Haile et al., 2016). Under this view, we would expect cashew farmers in Benin to reduce cultivated area in response to greater cashew price volatility.

A contrasting view, more suitable for our setting, suggests that price volatility may instead increase cultivation, particularly in developing country settings where factor markets imperfections are pervasive (Barrett, 1996). The idea is that when prices are volatile, smallholders over-allocate inputs to crop production because outside options are low and they need to secure income under uncertainty. This over-allocation is especially salient among farmers already specialized in the crop. By contrast, large farms cut back on risky production under volatility, consistent with Sandmo (1971), because their opportunity cost of committing inputs to a risky crop is higher.

The Barrett (1996) view fits our context well and helps rationalize our seemingly counterintuitive first stage estimates (Table A7). Cashew production in Benin is dominated by poor smallholders facing market frictions and limited risk-mitigation strategies (Degla, 2015). For these farmers, volatility can plausibly induce land expansion into cashews rather than contraction, especially among farmers with sunk investments in cashew orchards (proxied by baseline cashew land share in our analysis, i.e., the "share" of our shift-share IV). This interpretation can explain why our first stage runs counter to Sandmo but aligns with Barrett's mechanism under market failures. While few empirical studies test this alternative mechanism, the closest is Bellemare et al. (2020), which finds no empirical support for the Sandmo (1971) prediction.

A4 Appendix Tables

Share of New Cashew Plantations Not Classified as Forests			
Year	**15% Threshold**	**20% Threshold**	**25% Threshold**
2019	0.908	0.971	0.996
2020	0.950	0.997	0.999
2021	0.908	0.972	0.995

Table A3: Share of new cashew plantations not classified as forests.

Note: Cell values are the share of new cashew plantations (planted between the corresponding row year and the prior year) not classified as forests by VCF. VCF pixel values (percent forest) are classified as forest if they are above the threshold (columns).

Table A4: Correlation: Cashew Proximity, Household Wealth, and Forest Cover

	(1) Wealth Index	(2) Log EVI
Near Cashew (=1)	0.330**	-0.020***
	(0.154)	(0.003)
Household Controls	Yes	Yes
Geography Controls	Yes	Yes
Outcome Mean	3.004	8.118
Arrondissement FEs	✓	✓
Observations	2866	2866
R^2	0.512	0.985

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are a household cross section. The outcome in column 1 is household wealth on a scale of 1-5. Column 2 is log EVI in a small radius around households (2km radius for rural and 10km for urban). "Near Cashew" indicates whether households' DHS cluster is less than the median distance to the nearest cashew plantation. Regressions include survey weights and controls for household size, language, rain, temperature, lat/lon, and nightlights. Standard errors are heteroskedasticity-robust.

Table A5: TWFE: Cashew Coverage, Local Income, and Forest Cover

	(1) Log NTL	(2) Log GDP	(3) Forest Share
CashewShare_{adt}	0.376**	0.062	-0.031***
	(0.172)	(0.077)	(0.011)
Controls	Yes	Yes	Yes
Data Source	✓	✓	✓
Arrondissement FEs	✓	✓	✓
Department × Year FEs	412	412	412
Observations	0.977	0.857	0.882

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. Coefficients are estimated via OLS. Outcomes are transformed by $log(x + 0.01)$ to account for zero values. Column 1 is nightlight radiance, column 2 is GDP per capita from Rossi-Hansberg and Zhang (2025), and column 3 is forest share of land area. "Cashew share" is the fraction of arrondissement land area under cashews. All specifications control for rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A6: Test for Pre-Trends

Outcomes are for time $t-1$	(1) Log NTL	(2) Log GDP	(3) Forest
Shift-share (time t)	0.043	0.019	-0.005
	(0.040)	(0.024)	(0.003)
Controls	Yes	Yes	Yes
Arrondissement FEs	✓	✓	✓
Department × Year FEs	✓	✓	✓
Observations	309	309	309
R^2	0.984	0.887	0.892

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. Outcomes are lagged by one period. "Shift-share" is the interaction of global cashew price variance with baseline cashew share of land area. Controls include price level interacted with baseline cashew share, agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A7: First Stage Estimates

Outcome: Cashew share of land area	(1)	(2)	(3)	(4)	(5)	(6)
Log Volatility × Baseline Cashew Share	0.057*** (0.013)	0.062*** (0.014)	0.062*** (0.014)	0.134*** (0.030)	0.172** (0.074)	0.232*** (0.059)
Log Price × Baseline Cashew Share	No	Yes	Yes	Yes	Yes	Yes
Agrochemicals	No	No	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Volatility Measure	Var	Var	Var	SD	CV	Roll
Arrondissement FEs	✓	✓	✓	✓	✓	✓
Department × Year FEs	✓	✓	✓	✓	✓	✓
KP (2006) F-Stat	18.65	20.17	19.84	19.43	5.40	15.62
Observations	412	412	412	412	412	412

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. The outcome is land area under cashews. Volatility is measured as variance (columns 1-3), standard deviation (column 4), coefficient of variation (column 5), and 6-month rolling variance (column 6). "Baseline Cashew Share" is cashew land share in 2015. "Price" is global average monthly prices in year t. All specifications include controls for agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A8: Robustness to Alternative Volatility Measures

	Outcome: Log NTL			Outcome: Log GDP			Outcome: Forest Share		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CashewShare_{adt}	0.124 (0.965)	-1.817 (1.898)	0.007 (0.973)	0.516 (0.406)	1.493 (0.953)	0.575 (0.422)	-0.272*** (0.070)	-0.247** (0.124)	-0.270*** (0.070)
Log Price × Baseline Cashew Share	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agrochemicals	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV Volatility Measure	SD	CV	Roll	SD	CV	Roll	SD	CV	Roll
Arrondissement FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department × Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
KP (2006) F-Stat	19.43	5.40	18.75	19.43	5.40	18.75	19.43	5.40	18.75
Observations	412	412	412	412	412	412	412	412	412

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. "Cashew Share" is land share under cashew cultivation, instrumented with global cashew price volatility interacted with baseline cashew share. Price volatility measures include standard deviation (columns 1, 4, 7), coefficient of variation (columns 2, 5, 8), and rolling volatility (column 3, 6, 9). "Price" is global average monthly prices in year t. All specifications include controls for agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A9: Robustness Tests: Log GDP

	(1)	(2)	(3)	(4)
$\text{NumberPlantations}_{adt}$	0.025			
	(0.022)			
CashewShare_{adt}		0.571	1.028	0.436
		(0.477)	(0.660)	(0.447)
Log Volatility $\times$ Baseline Crop Share	No	Yes	No	No
Log Price $\times$ Baseline Cashew Share	Yes	Yes	Yes	Yes
Agrochemicals	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Linear Trend	No	No	No	Yes
Arrondissement FEs	✓	✓	✓	
Department $\times$ Year FEs	✓	✓	✓	✓
Price Data	FAO	FAO	INDFC	FAO
Observations	412	412	412	412
F-Statistic	19.03	16.94	9.45	14.91

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. The outcome is GDP per capita and transformed by $log(x + 0.01)$ to account for zero values. "NumberPlantations" is number of cashew plantations per km2 in an arrondissement. "CashewShare" is land share under cashews. Both are instrumented with global cashew price variance interacted with baseline cashew share. "Volatility" is measured by price variance. "Price" is global average monthly prices in year t. "CropShare" is land area under non-cashew crops. All specifications include controls for agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A10: Robustness Tests: Log Nightlights

	(1)	(2)	(3)	(4)
$\text{NumberPlantations}_{adt}$	0.015			
	(0.055)			
CashewShare_{adt}		-0.298	1.090	0.134
		(1.105)	(1.048)	(1.130)
Log Volatility × Baseline Crop Share	No	Yes	No	No
Log Price × Baseline Cashew Share	Yes	Yes	Yes	Yes
Agrochemicals	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Linear Trend	No	No	No	Yes
Arrondissement FEs	✓	✓	✓	
Department × Year FEs	✓	✓	✓	✓
Price Data	FAO	FAO	INDFC	FAO
Observations	412	412	412	412
F-Statistic	19.03	16.94	9.45	14.91

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. The outcome is nightlight radiance and transformed by $log(x + 0.01)$ to account for zero values."NumberPlantations" is number of cashew plantations per km2 in an arrondissement. "CashewShare" is land share under cashews. Both are instrumented with global cashew price variance interacted with baseline cashew share. "Volatility" is measured by price variance. "Price" is global average monthly prices in year t. "CropShare" is land area under non-cashew crops. All specifications include controls for agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A11: Robustness Tests: Forest Share of Land Area

	(1)	(2)	(3)	(4)
NumberPlantations$_{adt}$	-0.016***			
	(0.004)			
CashewShare$_{adt}$		-0.304***	-0.290**	-0.268***
		(0.088)	(0.129)	(0.080)
Log Volatility $\times$ Baseline Crop Share	No	Yes	No	No
Log Price $\times$ Baseline Cashew Share	Yes	Yes	Yes	Yes
Agrochemicals	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Linear Trend	No	No	No	Yes
Arrondissement FEs	✓	✓	✓	
Department $\times$ Year FEs	✓	✓	✓	✓
Price Data	FAO	FAO	INDFC	FAO
Observations	412	412	412	412
F-Statistic	19.03	16.94	9.45	14.91

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. The outcome is forestland share. "NumberPlantations" is number of cashew plantations per km2 in an arrondissement. "Cashew-Share" is land share under cashews. Both are instrumented with global cashew price variance interacted with baseline cashew share. "Volatility" is measured by price variance. "Price" is global average monthly prices in year t. "CropShare" is land area under non-cashew crops. All specifications include controls for agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A12: Robustness: Alternative First Stage and Reduced Form

	First Stage	Reduced Form	
	(1) Cashew	(2) Log GDP	(3) Forest Share
Log Price Level	0.051	-0.014	-0.027
× Baseline Cashew Share	(0.081)	(0.090)	(0.036)
Agrochemicals	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Arrondissement FEs	✓	✓	✓
Department × Year FEs	✓	✓	✓
KP (2006) F-Stat	0.40		
Observations	412	412	412
R^2		0.906	0.880

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Table shows alternative first stage and reduced form estimates using price level to construct the shift-share instrument instead of price volatility. "Price Level" is global average monthly prices in year t. "CashewShare" is land share under cashews. Column 1 is the first stage where the outcome is land share under cashew cultivation. Remaining columns are reduced form estimates where the outcomes are either log GDP per capita or forest share. All specifications include controls for agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A13: Mechanisms: Cashew Exposure and Household Wealth

	(1) Wealth	(2) Toilet	(3) Elec.	(4) Fridge	(5) Educated
Land owner	-0.589***	-0.035***	-0.105***	-0.025*	-0.139***
	(0.067)	(0.011)	(0.031)	(0.014)	(0.031)
Near Cashew × Land owner	0.224**	0.040***	0.075*	0.026	0.097**
	(0.095)	(0.013)	(0.041)	(0.017)	(0.043)
Near Cashew (=1)	0.266*	-0.062**	0.134**	-0.030	-0.055
	(0.158)	(0.026)	(0.067)	(0.031)	(0.070)
Household Controls	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes
Arrondissement FEs	✓	✓	✓	✓	✓
Observations	2866	2866	2866	2866	2866
R^2	0.533	0.210	0.367	0.099	0.194

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are a household cross section of DHS data. "Landowner" indicates if the household owns farmland. "Near Cashew" indicates whether the household's DHS cluster is below median distance to the nearest cashew plot. The outcome in column 1 is a wealth index between 1-5. Remaining columns are indicators for having a flush toilet, electricity, fridge, and an educated (> secondary school) household head. All regressions include survey weights and controls for household size, language, rain, temperature, lat/lon, and nightlights. Standard errors are heteroskedasticity-robust.

Table A14: Mechanisms: Alternative High-Resolution GDP Data

	(1) Log GDP
CashewShare_{adt}	0.134***
	(0.045)
Controls	Yes
Data Source	✓
Arrondissement FEs	✓
Department × Year FEs	206
Observations	0.998

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level for 2015 and 2019. The outcome is GDP per capita from Chen et al. (2022), transformed by $log(x + 0.01)$ to account for zero values. "Cashew share" is the fraction of arrondissement land area under cashews. All specifications control for rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

Table A15: Mechanisms: Robustness of Income Volatility to Electricity Grid Fixed Effects

	(1) Variance	(2) Std. Dev.	(3) Coeff Var.	(4) Rolling
CashewShare_{adt}	-0.729	-0.659	-1.594**	-0.715
	(0.757)	(0.524)	(0.782)	(0.742)
Log Price × Baseline Cashew Share	Yes	Yes	Yes	Yes
Agrochemicals	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Arrondissement FEs	✓	✓	✓	✓
Department × Year FEs	✓	✓	✓	✓
Transmission Network FEs	✓	✓	✓	✓
KP (2006) F-Stat	9.23	9.23	9.23	9.23
Observations	412	412	412	412

Note: * $p < .1$, ** $p < .05$, *** $p < .01$. Data are at the arrondissement-year level. Outcomes are log of annualized monthly nightlight volatility measured by variance (column 1), standard deviation (column 2), coefficient of variation (column 3), and 6-month rolling variance (column 4). "CashewShare" is the fraction of cells with cashew plantations, instrumented with the interaction of global cashew price variance with baseline cashew coverage. All regressions include fixed effects for the dominant electricity transmission line in the arrondissement and as well as controls for price level interacted with baseline cashew coverage, agrochemical use, rain, temperature, and drought intensity. Standard errors clustered by arrondissement.

A5 Appendix Figures

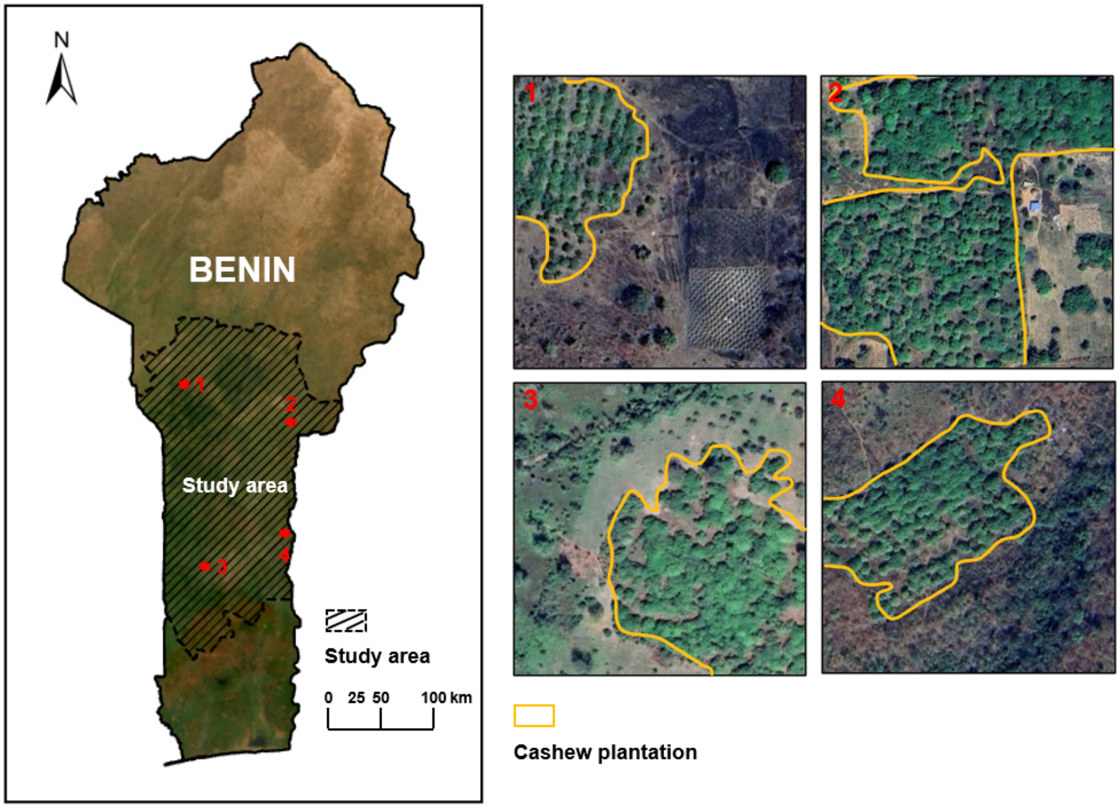

Figure A1: Cashew Plot Delineation

Note: Left panel shows the study area along with four example cashew plantations (red points). Right panel shows high resolution classification model output (see Section 3.1 in main text).

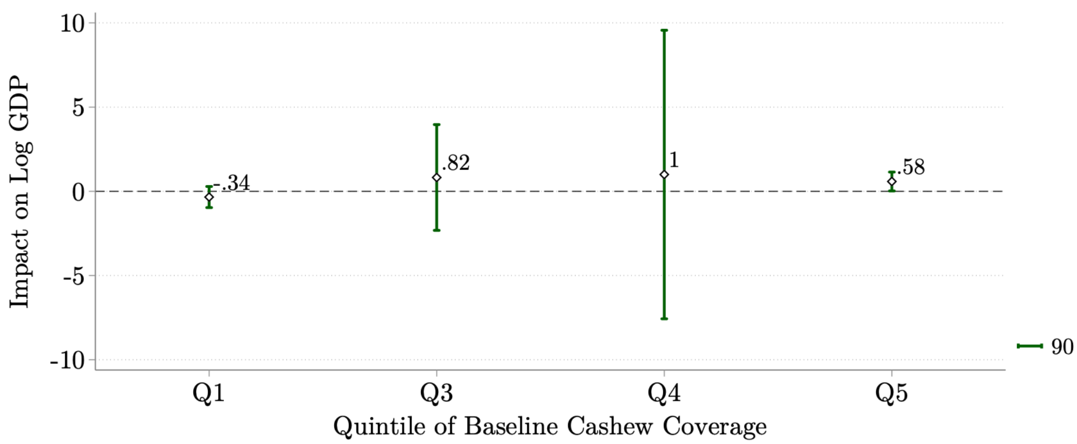

Figure A2: IV Estimates by Quintiles of Baseline Cashew Coverage

Note: White diamonds are coefficients from the second stage equation (Equation 6) across quintiles of baseline cashew cover. Bars are 90 percent confidence intervals. All specifications control for price levels, agrochemical use, rain, temperature, and drought intensity. Q2 is omitted from presentation due to overly large standard errors which warp the graph scale. Standard errors clustered by arrondissement.

References

Barrett, Christopher B, "On price risk and the inverse farm size-productivity relationship," *Journal of Development Economics*, 1996, *51* (2), 193–215.

Bellemare, Marc F, Yu Na Lee, and David R Just, "Producer attitudes toward output price risk: Experimental evidence from the lab and from the field," *American Journal of Agricultural Economics*, 2020, *102* (3), 806–825.

Chen, Jiandong, Ming Gao, Shulei Cheng, Wenxuan Hou, Malin Song, Xin Liu, and Yu Liu, "Global 1 km$\times$ 1 km gridded revised real gross domestic product and electricity consumption during 1992–2019 based on calibrated nighttime light data," *Scientific Data*, 2022, *9* (1), 202.

Degla, Pamphile, "Technical efficiency in producing cashew nuts in Benin's Savanna zone, West Africa," *Quarterly Journal of International Agriculture*, 2015, *54* (2), 117–132.

Gibson, John, Susan Olivia, and Geua Boe-Gibson, "Night lights in economics: Sources and uses 1," *Journal of Economic Surveys*, 2020, *34* (5), 955–980.

Haile, Mekbib G., Matthias Kalkuhl, and Joachim von Braun, "Worldwide Acreage and Yield Response to International Price Change and Volatility: A Dynamic Panel Data Analysis for Wheat, Rice, Corn, and Soybeans," *American Journal of Agricultural Economics*, 2016, *98* (1), 172–190.

Hansen, Matthew C, Peter V Potapov, Rebecca Moore, Matt Hancher, Svetlana A Turubanova, Alexandra Tyukavina, David Thau, Stephen V Stehman, Scott J Goetz, Thomas R Loveland et al., "High-resolution global maps of 21st-century forest cover change," *science*, 2013, *342* (6160), 850–853.

Krah, Kwabena, "Maize price variability, land use change, and forest loss: evidence from Ghana," *Land Use Policy*, 2023, *125*, 106472.

Lundberg, Clark and Ryan Abman, "Maize price volatility and deforestation," *American Journal of Agricultural Economics*, 2022, *104* (2), 693–716.

Rossi-Hansberg, Esteban and Jialing Zhang, "Local GDP Estimates Around the World," Technical Report, National Bureau of Economic Research 2025.

Sandmo, Agnar, "On the theory of the competitive firm under price uncertainty," *The American Economic Review*, 1971, *61* (1), 65–73.

Sika, K Chabi, H Adoukonou-Sagbadja, LE Ahoton, I Adebo, FA Adigoun, A Saidou, SO Kotchoni, A Ahanchede, and L Baba-Moussa, "INdigenous Knowledge and Traditional Management of Cashew," *Journal of Experimental Biology and Agricultural Sciences*, 2013, *1*, 5.

Townshend, John, Matthew Hansen, Mark Carroll, Charlene DiMiceli, Robert Sohlberg, and Chengquan Huang, "Annual global automated MODIS vegetation continuous fields (MOD44B) at 250 m spatial resolution for data years beginning day 65, 2000-2014, collection 5 percent tree cover, version 6.," Technical Report, University of Maryland, College Park 2017.