

Hindcasting the last decade: calibrating a novel, recursive dynamic land-use explicit CGE model

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Abstract

Equilibrium models (EM) solve constrained optimization problems and have long been used within trade analyses to examine the potential impacts of specific policy changes. More recently they have been incorporated into the foundation of process-based integrated assessment models. Within this study we develop a novel, recursive dynamic land-use explicit CGE model using the most recent economic and land-use data available to build confidence in the model's ability to predict land-use change under different socioeconomic trajectories. We find that land-use as predicted by the model is highly sensitive to the choice of land supply elasticity as well as magnitude of labor supply shock. The considerable degree of data collection and harmonization coupled with a series of dynamic runs across the 2011 to 2020 period allowed us to test this model against the historical record and gain new insight into roles of select parameters and exogenous variable specification. Our fully calibrated model robustly simulates land-use over a 9 year period given demographic and GDP drivers. The current study highlights the importance of conducting hindcasting runs in order to compare model outputs with the historical record. This work also serves as the proof-of-concept for a new economic land-use model capable of simulating long-term paths of economic growth and associated changes in land-use.

1. Introduction

Equilibrium models (EM) solve constrained optimization problems and have long been used within trade analyses to examine the potential impacts of specific policy changes. Although they have been employed in a wide variety of applications, EMs are typically temporally static and limited to uniform shocks on a single variable of interest [1]. More recently they have been incorporated into

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the foundation of process-based integrated assessment models (IAM) [2] to drive growth at the sectoral level according to socioeconomic scenario storylines such as the Shared Socioeconomic Pathways (SSPs) [3]. Within the IAM context, EMs necessarily adopt temporally dynamic approaches to encompass long-term time horizons consistent with the Representative Concentration Pathways (RCPs) and allow for the pairing of feasible SSP-RCP pathways [4, 5]. These pairings help facilitate comparisons of IAM outputs across a wide range of economic, climate, and land-use indicators [6].

Although the SSP-RCP framework was intended to provide a set of common assumptions among various modeling communities [7], the differing structures of each IAM in terms of models used (e.g., partial equilibrium vs. computable general equilibrium), model coupling, and a lack of consensus on input variables have been an obstacle to their deployment in policy-making [8]. These disparities are perhaps best illustrated in the wide range of land-use trajectories produced by each model [9], evident during the historical period in which they were calibrated and more predictably over long run projections. While these critiques are valid, it is worth taking into consideration the full ambition of a SSP run which ostensibly brings together economic and demographic drivers to simulate a cohesive narrative of how the world may change over the next 80 years.

The long-term 2100 time horizon has been in a sense imposed on the IAM community by the need to more accurately model greenhouse gas emissions [10] which vary as a function of economic growth, technology, and land-use among other dimensions. And while the climate change modeling community has done remarkably well historically speaking [11], bringing in a human component introduces many new uncertainties. In full recognition of these uncertainties and the highly theoretical task of simulating the long-term trajectory of the global economy and its land-use implications through 2100, the current study first attempts to predict the known historical record (i.e., hindcast) and compare outputs to available data sources.

This work begins with the collection of the most recent economic and land-use data which is then used to produce an updated 2011 reference year for all subsequent model runs. A new model (hereafter referred to as TEEMS⁴, Section 2.2) is then constructed which uses historical GDP and demographic trajectories to produce change in physical land-use (i.e., hectares) during the hindcasting period. Building on innovation in land-use representation from Zhao et al. [12], TEEMS stands in contrast to the vast majority of GTAP-based models which only track the flow of land in terms of value (e.g., grain sector returns value to the land primary factor). Throughout these simulations a systematic sensitivity analysis on key variables and parameters is carried out to determine the configuration for each region which most closely tracked observed changes.

By driving the model with the same inputs as would be used to simulate future trajectories (i.e., demographic and economic growth as well as established behavioral parameters), we are able to gauge model performance on known

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output variables of interest throughout the hindcasting period (i.e., land-use) and select the best performing set of shocks and behavioral parameters. This process builds a foundation for simulating long-term socioeconomic pathways by establishing confidence in the model’s ability to robustly simulate land-use change into the future using socioeconomic drivers. Despite the relative scarcity of IAM hindcasting simulations [2], this study demonstrates the degree to which model calibration via hindcasting is a valuable technique given the considerable uncertainties involved in simulating land-use many decades into the future [13]. Throughout this analysis we seek to cast light on various aspects of CGE modelling including known sources of uncertainty as well as steps that are not often elaborated upon such as parameter aggregation methods.

2. Methods

We simulate the most recent historical period for which we have data (2011-2020) using a novel, temporally recursive computable general equilibrium (CGE) model with endogenous land supply (i.e., predicted by the model) and biophysical land flows (Section 2.2). There are several distinct steps to the current analysis which build sequentially upon each other. In order to track the historical record as closely as possible, the most recent data spanning economic, demographic, and land-use over the 2011-2020 period was collected and harmonized for the 232 countries encompassed within the GTAP model (Section 2.1). We then use this data to conduct a large static model run using the standard GTAP 6.2 model [14], rebasing the GTAP10a [15] 2011 reference year so that it more closely reflects current data (Section 2.4.1).

Following the rebase, the most recent FAO data on land-use, harvested land, and production analogous⁵ to data within the GTAP Land Use and Land Cover (LULC) Database is collected, replacing existing LULC-associated coefficients [16]. With our updated basedata for the 2011 reference year, we simulate the 2011-2020 period through 10 dynamic model runs using varied labor and capital supply shocks as well as 5 sets of land supply elasticity levels to determine which combination best represents land-use change throughout the last decade at the region level. A final hindcasting run is then carried out with the calibrated model.

2.1. Data

The quality of input data is paramount within CGE modelling since all shocks will be implemented against this initial state. While a more traditional CGE trade-focused analysis may examine the impact of a single changed variable (e.g., export tax) on other variables of interest (e.g., import demand among prominent receiving nations), CGE models within IAMs are responsible for providing outputs for downstream coupled models (e.g., earth system models)

⁵For the purposes of the current study we focus on the regional level and do not utilize agro-ecological zones.

across a wider array of drivers such as land-use, energy consumption, and food demand. Within this context, CGE model results are directly influenced by the baseline represented by economic data at a specific point in time, with the Global Trade Analysis Project (GTAP) being the most utilized source [17]. For this reason, we devote a single large-scale static run solely toward producing a new set of input data consistent with the most recent economic data.

Within the most recent GTAP release⁶ [GTAP 10a; 15], four reference years are provided based on the collection and harmonization of input-tables and macroeconomic data from a variety of sources including the World Bank and UN Comtrade Database. GDP figures within the 10a release are based on World Bank WDI data from July 22, 2016⁷ [18]. Due to subsequent revisions within the World Bank WDI database as well as the need to reconcile UN Comtrade trade data with GDP, database values within GTAP10a are not consistent with the most current macroeconomic data sources [19].

Although some degree of data revision is expected within such a time frame, many regions have been revised considerably (Table 1), complicating efforts to use this database as a base from which to simulate an economic trajectory which is already out of sync at the initial time step. While discrepancies with the most recent macroeconomic figures may be overlooked within static CGE analyses because they primarily focus on percent change deviations from a baseline given a specific policy change, large deviations from macroeconomic data (i.e., GDP and subcomponents such as private household expenditure) introduce inaccuracy into the calibration of temporally dynamic models — particularly when long-term absolute levels of consumption are subsequently generated. This is due to the way shocked variables are calculated by using an initial baseline value (e.g., Australian GDP in 2011) and a desired value in the subsequent time step (e.g., Australian GDP in 2012). Discrepancies within the baseline value directly impact the magnitude of associated shocks which in turn exert an influence on other variables.⁸ While some variables may only interact within select modules, change in GDP exerts a top-down impact on the entire model.

In order to address these inconsistencies, we update the existing GTAP 10a database [15] reference years through the collection and harmonization of macroeconomic data covering the 232 countries which make up 141 GTAP regions. Economic data encompassing GDP, and GDP subaggregates (see RHS, Equation 2) for the 2011-2020 period were gathered from several sources depending on availability in the following order of preference: World Bank WDI [20], World Bank Global Economic Prospects [2018-2024, depending on the region 21], FAOSTAT Database [22], Eurostat [23], IEDOM [24], and national statistical offices where necessary. World Bank data was given priority due their status as

⁶At the time of writing, the GTAP11 release is imminent.

⁷http://databank.worldbank.org/data/download/archive/WDI_excel_2016_07.zip

⁸One mental heuristic I use is to conceptualize the model as an inflated balloon within a semi-rigid structure determined by model equations. The force with which you would squeeze the balloon (apply shocks) to achieve a different shape depends on the dimensions of the original structure.

Table 1: GDP discrepancies greater than 10% among non-composite GTAP regions for the GTAP10a 2011 reference year compared to current World Bank WDI data. Values in million 2011USD. World Bank WDI figures from indicator code NY.GDP.MKTP.CD, accessed on August 19, 2022.

region	GTAP10a	WB WDI	% Deviation
Côte d’Ivoire	25381	36694	45
Malawi	5628	8004	42
Uganda	20263	27872	38
Benin	7816	10693	37
Paraguay	25071	33737	35
Guinea	5068	6785	34
Zimbabwe	10956	14102	29
Vietnam	135539	172596	27
Senegal	14441	17814	23
Madagascar	9893	11552	17
Cameroon	26587	30631	15
Oman	67938	77498	14
Nepal	18914	21574	14
Burkina Faso	10724	12080	13
El Salvador	23100	20284	−12
Kenya	41953	46869	12
Brunei	16692	18525	11
South Africa	416594	458202	10
Mozambique	13131	14382	10

the primary data source for GDP by GTAP and generally wide coverage of data across subaggregates.

All data was collected in or converted to 2015US\$ using World Bank (WB) GDP deflators (Indicator Code: NY.GDP.DEFL.ZS) or data provided by national statistical offices. Where macroeconomic data was unavailable or obviously inconsistent, gaps were filled either through a process of deduction using the GDP-associated equations (e.g., Equation 2) or by applying the percentage change over time of mean values at the World Bank 23 region mapping level to available data points⁹. In the few cases where data was completely missing (e.g., Western Sahara), data was calculated using per capita GDP in a similar region (Morocco) applied to known data points (in this case population growth). Demographic data was taken from the IIASA World Population Program [25–27] and UN Population Division [28]. Since the most recent demographic trajectories begin at year 2015, data for pre-2015 years was calculated by applying year-over-year change from older sources spanning the 2011-2015 period to current 2015

⁹Melanesia, Micronesia, and Polynesia were aggregated into a single ‘Oceania’ aggregate due to the relatively small number of countries in these regions

data.

In terms of data gathering and harmonization, our methodology differs from the original GTAP database construction where priority is given to trade data and other sources of consumption are scaled to produce the desired trade-to-GDP ratio [see 19]. This adherence to WB indicators across all components allows us to harmonize GDP with the most recent economic data and reflects our focus on consumption within the entire economy. Finally, we collect the most recent FAOSTAT pertaining to the GTAP LULC Database data for land cover, harvested land, and crop production.¹⁰ Forestland as utilized within the GTAP LULC Database [16, 29] has no direct equivalent within FAOSTAT and therefore no pre-model modifications are undertaken. In the case of crop production, data was mapped and aggregated to GTAP sector categories using the associated GTAP to UN CPC v2.1 Concordances.¹¹

2.2. Model

Within the current chapter, 12 model runs are conducted using the GTAP 6.2 and TEEMS model (Table 4). The GTAP model used here (GTAP 6.2, Model Run No. 1, [14]) is well represented within equilibrium modelling applications [1] and forms the base for many specialized variants [e.g., GTAP-BIO, GTAP-INT; 30, 31]. The current analysis introduces TEEMS which is a modified version of the explicit technological change variant presented in Zhao et al. (Table 1, E4) [12]. We also draw from Pleven et al. [32] in respect to implementing additional equations pertaining to agriculture and crop production. Here we present the new model with an emphasis on departures from its original specifications (see Table 2).

In order to move the model forward in time, we use a recursive dynamic approach consisting of multiple sequential static runs where updated coefficients from the initial time step ($t = 0$) are used as input data for the next time step ($t + 1$). Parameter values remain constant across all time steps and coefficients that do not comprise input data are recalculated at each step. As the model progresses toward the final time step only shocks within the current time step influence endogenous variables (cf. intertemporal dynamics).

The [12] model was chosen as a base for TEEMS due to the significant advances in tracking not only value flows (as in all equilibrium models) but also associated biophysical land flows through the implementation of an additive constant elasticity of transformation (ACET) function. The ACET function builds on past work with additive elasticity of substitution within the labor supply [33, 34] to preserve the total physical area under agricultural production (compared to effective land denominated in monetary value) and allow for more direct targeting of land use policies [12]. Used in conjunction with the GTAP Land Use and Land Cover Database [16] or other sources (e.g., FAOSTAT),

¹⁰These are "LCOV", "AREA", and "TONS".

¹¹2011 land-use values for Sudan and South Sudan were replaced with 2012 values due to the 10 fold increase between data in these years.

Table 2: A comparison of the Zhao et al. (2020) model and TEEMS across core components.

component	Zhao (2020)	TEEMS
database/year	GTAP 9/2011	GTAP10a rebased/2011
temporal dynamics	static	recursive
no. time steps	1	9
no. regions	3	117
no. sectors	7	7
no. primary factors	4	4
land supply	exogenous	endogenous
asymptote	No	Yes
CET	additive	additive
software	GEMPACK	CGEPACK
solution method	Gragg	Midpoint
no. steps	2-4-6	2-4-8
no. subintervals	2	20
solver	LU decomposition	SBBD
no. coefficients/variables	206/254	182/178
no. shocked variable(s)	1	3-4
shock type	uniform	heterogeneous

this allows for the explicit tracking of biophysical land flows among managed¹² land-use types. This development reduces the need for post-model land-use area calculations and other ad-hoc coupled model approaches which represent a significant source of uncertainty in land-use focused economic modelling. For example, within coupled model framework, this deficit has often been addressed through ‘ad hoc’ ex-post treatments [e.g., 35] and outsourcing of biophysical land calculation to downstream models [e.g., 36, 37].

The current model builds on [12] by increasing model size, implementing an asymptote and endogenizing land supply (Section 2.2.1), and adopting temporally recursive dynamics (Table 2). Further, additional region-specific parameter values for cropland (see Table 3) were gathered from existing literature. The structure of the nested land supply in terms of land-use and associated managed land-use categories (cropland, pastureland, and forestland) has not been modified and we retain the ACET values presented in the original model.

2.2.1. Land supply

Land supply¹³ represents managed land being utilized by an economic sector. Within the standard model it is typically exogenous and not shocked given the static nature of the GTAP model. However, within a dynamic analysis focused

¹²Managed land-use indicates that an economic activity takes place while no such activity occurs on unmanaged land.

¹³qo(“land”,REG) within the standard GTAP model

on long-term change, the assumption of no change in land supply (i.e., exogenous land supply with no shock) is not tenable. Endogenization of land supply through region-specific land supply curves allows for the flow of unmanaged to managed land based on dynamic land rents and the potential for conversion to cropland based on biophysical availability [38, 39]. While it is possible to develop land supply trajectories and use these to exogenously guide the land primary factor, we endogenize land supply through the implementation of land supply elasticities (E in Equation 1) coupled with an asymptote (Γ) as originally presented in the Magnet Model [40].

Within TEEMS, a single land category is used in order to utilize existing data to calculate a region-specific land asymptote which represents the total area of potential land not currently under management that could feasibly come into agricultural management [39]. The asymptote is a fundamental constraint on the area of land that can come into management. As the price of land (p) changes, it interacts with the land supply elasticity and the ratio of the asymptote (Γ) to land already in management (A), resulting in a new value for land supply (s).

$$s = (\Gamma/A) + (E * p) \quad (1)$$

In order to calculate an asymptote for the 2011 reference year we apply shares of current agricultural land in total available and suitable land [Table 3, 41] to 2011 FAOSTAT values for agricultural land in each region.¹⁴ Within our recursive model the asymptote decreases as land is taken into management. This effectively reduces the magnitude of conversion in subsequent time steps by requiring a larger land price increase as more land comes into management, all else being equal.

Land supply elasticities are required in addition to the asymptote in order to endogenize land supply. The region-specific land supply elasticity is a highly uncertain parameter which has been calculated with a variety of methods [see e.g., 42]. Broadly speaking, the land supply elasticity represents the propensity to bring land into management given a change in the price of land (i.e., land rent). For the purposes of this study we use the land supply elasticity values in [42], with the exception that we adopt the approach of Laborde et al. [43] and lower the elasticity in countries that have experienced increased agricultural returns *and* no increase in agricultural land area from 0.015 to 0.01.

2.3. Data and parameter aggregation

The TEEMS model has been aggregated to maximize the number of regions represented while retaining important distinctions within agricultural sectors. The full production structure includes 117 regions, 7 tradable sectors, and 4 primary factors which include a single "land" factor (Figure 1). Regions (Table 5) were aggregated where a sizable agricultural area was not present (e.g., UAE, Bahrain, Qatar), land area was subsumed within a larger territorial area (e.g.,

¹⁴Item: "Agricultural land", Item Code: 6610

South Africa, Lesotho, Eswatini), or where negligible economic and land-use activity takes place (e.g., Rest of World, Rest of North America). Sectoral aggregation (Table 6) is carried out along well-established high-level industries (e.g., manufacturing and services) as well as within crop sectors according to C_3 and C_4 fixation which is broadly consistent¹⁵ with the crop functional types employed within the Land-use Harmonization Project [44].

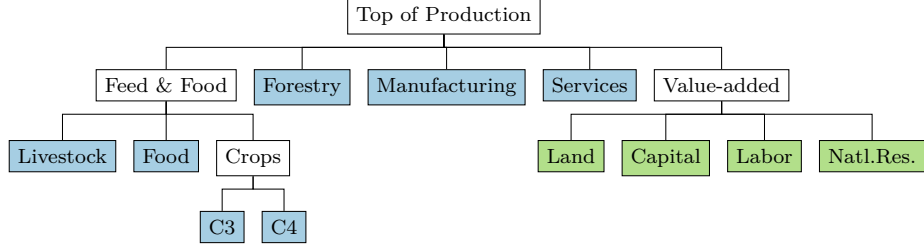


Figure 1: Production nesting structure. Blue shading denotes a traded commodity (set ID: TRAD_COMM). Green shading indicates a factor of production (set ID: ENDW_COMM).

The current analysis employs two distinct models with additional parameters necessary for the land-use explicit model (Table 3). Although parameter aggregation is necessary within all CGE model runs, there is typically little focus within studies with respect to the aggregation methodology. In the case of region- and sector-specific parameters, using the mean value of parameters will not yield accurate results if the initial parameter values vary and associated data values to be aggregated are not uniformly distributed. Within the current study we develop a reproducible methodology for aggregating parameter values (see Appendix B, Section 6.2) based on the original parameter values, the desired mapping, and the weighted sum of associated coefficients. While a sensitivity analysis was carried out on the land supply parameter, it was not practical given time and computing constraints to carry out a more comprehensive test on the remaining parameters.

2.4. Methodological approach

The model runs conducted within this study (Table 4) build sequentially upon each other in order to carry out a final calibrated hindcasting run using the most accurate data possible. The initial step establishes updated reference year data (Model Run 1, Section 2.4.1) which is used as the base for all subsequent model runs. We then systematically vary the land supply parameter (Model Runs 2a-2b, Section 2.4.2) by $\pm 20\%$ and $\pm 50\%$ under two sets of shocks: labor supply shocks calculated at 100% of the GDP shock and capital supply shocks at 25% (Model Runs 2a) and labor and capital supply shocks each calculated at 25% of the GDP shock (Model Runs 2b). In the final hindcasting run (Model

¹⁵Note that the GTAP sector “Other Grains” contains some C_3 crops however the vast majority in terms of land and value (e.g., maize) are C_4 .

Table 3: Headers, descriptions, and index ranges for parameters and associated data within the standard GTAP model and/or LULC model. † indicates LULC-specific parameter.

	Header	Description	Set Index	Source
Param.				
σ_F	EFED†	Elasticity in substitution of feed production	$j \in \text{ALL_INDS}, r \in \text{REG}$	[12]
σ_D	ESBD	Armington CES for domestic/imported allocation	$i \in \text{TRAD_COMM}$	[15]
σ_M	ESBM	Armington CES for regional allocation of imports	$i \in \text{TRAD_COMM}$	[15]
σ_T	ESBT	Elsct. of intermediate input substitution	$j \in \text{ALL_INDS}, r \in \text{REG}$	[15]
σ_A	ESBV	CES between primary factors in production	$j \in \text{ALL_INDS}, r \in \text{REG}$	[15]
η	ETA†	Elasticity of effective land over harvested area	$i \in \text{ENDWL_COMM}, r \in \text{REG}$	[45]
	ETL1†	Elsct. of transformation between forestry and agriculture		[12]
	ETL2†	Elsct. of transformation between pastures and crops		[12]
	ETL3†	Elsct. of transformation among crops		[12]
	ETRE	CET between sectors for sluggish primary factors	$i \in \text{ENDW_COMM}$	[15]
γ	INCP	CDE expansion parameter	$i \in \text{TRAD_COMM}, r \in \text{REG}$	[12]
λ	LSPY†	Elsct. of acreage expansion between managed & unmanaged land	$r \in \text{REG}$	[42]
	RFLX	Expected rate of return flexibility parameter	$r \in \text{REG}$	[15]
β	SUBP	CDE substitution parameter	$i \in \text{TRAD_COMM}, r \in \text{REG}$	[12]
	YD01†	Turn off the yield calibrated ESBVAs by setting to zero	$j \in \text{ALL_INDS}, r \in \text{REG}$	[12]
θ	YDEL†	Scalar yield elasticity target	$r \in \text{REG}$	[46]
Data				
	EVFA	Endowments - Firms Purchases at Agents' Prices	$i \in \text{ENDW_COMM}, j \in \text{PROD_COMM}, r \in \text{REG}$	[15]
	LCOV†	Land Cover/Use (1000 hectares)	$i \in \text{ENDWL_COMM}, j \in \text{LAND_USE}, r \in \text{REG}$	[16]
	TONS†	Production (1000 metric tonnes)	$i \in \text{ENDWL_COMM}, j \in \text{CROPS_COMM}, r \in \text{REG}$	[16]
	VDFA	Intermediates - Firms' Domestic Purchases at Agents' Prices	$i \in \text{TRAD_COMM}, j \in \text{PROD_COMM}, r \in \text{REG}$	[15]
	VDGA	Intermediates - Government Domestic Purchases at Agents' Prices	$i \in \text{TRAD_COMM}, j \in \text{REG}$	[15]
	VDPA	Intermediates - Household Domestic Purchases at Agents' Prices	$i \in \text{TRAD_COMM}, j \in \text{REG}$	[15]
	VIFA	Intermediates - Firms' Imports at Agents' Prices	$i \in \text{TRAD_COMM}, j \in \text{PROD_COMM}, r \in \text{REG}$	[15]
	VIGA	Intermediates - Government Imports at Agents' Prices	$i \in \text{TRAD_COMM}, r \in \text{REG}$	[15]
	VIPA	Intermediates - Household Imports at Agents' Prices	$i \in \text{TRAD_COMM}, r \in \text{REG}$	[15]

Run 3) we retain the baseline land supply elasticity value and 25% shocks to capital, varying the labor supply shock between 100% and 25% depending on which value resulted in agricultural land-use change closest to FAOSTAT values in 2020. This final run serves as the proof-of-concept for the new model.

Table 4: Model runs conducted within the current study. All runs except for No. 1 were recursive, spanning the 2011-2020 period. LSPY is the land supply elasticity. "-" indicates that the shocked variable is exogenous in the standard closure and requires no swap. Parentheses following a variable indicates that the shock takes place over a subset of the full variable set. Variable names correspond to the following descriptions: *pop* - population; *qgdp* - GDP; *aoreg* - output augmenting tech change; *afreg* - factor augmenting tech change; *yp* - private household consumption; *yg* - government expenditure; *dppriv* - private consumption distribution parameter; *dpgov* - government consumption distribution parameter; *qo* - primary factor supply;

No.	Model	LSPY	Labor Shk	Capital Shk	Shocked/Swapped Variables
1	GTAP 6.2	NA	NA	NA	qgdp/aoreg; yp/dppriv; yg/dpgov
2a	TEEMS	baseline	100%	25%	pop/-; qo("labor",REG)/-; qgdp/afreg
2a.p20	TEEMS	-20%	100%	25%	pop/-; qo("labor",REG)/-; qgdp/afreg
2a.n20	TEEMS	+20%	100%	25%	pop/-; qo("labor",REG)/-; qgdp/afreg
2a.p50	TEEMS	+50%	100%	25%	pop/-; qo("labor",REG)/-; qgdp/afreg
2a.n50	TEEMS	-50%	100%	25%	pop/-; qo("labor",REG)/-; qgdp/afreg
2b	TEEMS	baseline	25%	25%	pop/-; qo("labor",REG)/-; qo("capital",REG)/-; qgdp/afreg
2b.p20	TEEMS	-20%	25%	25%	pop/-; qo("labor",REG)/-; qo("capital",REG)/-; qgdp/afreg
2b.n20	TEEMS	+20%	25%	25%	pop/-; qo("labor",REG)/-; qo("capital",REG)/-; qgdp/afreg
2b.p50	TEEMS	+50%	25%	25%	pop/-; qo("labor",REG)/-; qo("capital",REG)/-; qgdp/afreg
2b.n50	TEEMS	-50%	25%	25%	pop/-; qo("labor",REG)/-; qo("capital",REG)/-; qgdp/afreg
3	TEEMS	baseline	varied	25%	pop/-; qo("labor",REG)/-; qo("capital",REG)/-; qgdp/afreg

2.4.1. Updating the 2011 reference year

Rebasing the reference year entails applying heterogeneous shocks to the GTAP 2011 reference year data based on the gathered data for 2011. Similar

approaches have been applied in previous studies [e.g., 47] to transition one reference year (2007) to a future point in time (2030) where a subsequent simulation is then carried out. The 2011 reference year was chosen in order to provide a span of 9 output years from which to compare to the historical record. The rebase takes place across 3 region-specific variables and their associated coefficients (Table 4; Equation 2): $qgdp$ (GDP, gross domestic product), yp (C, private household consumption), and yg (G, government expenditure).¹⁶ By exogenously adjusting GDP, private household consumption, and government expenditure, the model forces regional investment (I), exports (E), and imports (M) to adjust in order to satisfy Equation 2.¹⁷

$$\underbrace{qgdp}_r = \underbrace{yp}_r + \underbrace{yg}_r + I_r + (E_r - M_r) \quad (2)$$

In order to alter GDP, we endogenize “aoreg” which represents region-specific output augmenting technological change. This variable is chosen rather than “afreg” (factor augmenting technological change) in order to be conceptually consistent with underlying theory — that being a change in GDP which is not necessarily incurred through any change in primary factor productivity.¹⁸ Experiments were also undertaken to apply sectorally uniform, region-specific¹⁹ shocks²⁰ to both total exports and imports however the accuracy of these model runs was found to be unacceptable. Further, given the trade-focused nature of the GTAP model, it is more conceptually sound²¹ to allow the model to solve for trade-related variables heterogeneously rather than impose a top-down uniform shift which may not be theoretically feasible when applied over all regions.

2.4.2. Land supply sensitivity analysis and hindcasting run

Following the reference year update, a series of recursive runs (Model Runs 2 and 3) using systematically varied land supply sensitivities were carried out to simulate the historical record. Region-specific exogenous GDP, private household consumption, and government expenditure trajectories guide the model throughout the entire course of the model run. All other model inputs including shocks were identical, allowing the model output to reflect the sole impact of the land supply parameter. Population was simulated through shocks to the “pop” variable and retained through subsequent runs for diagnostic purposes via a population-specific coefficient. We use the SSP2 population trajectories for this study (small divergences between SSPs begin in 2016). GDP is driven by

¹⁶For a similar swap/closure, see [48].

¹⁷Associated GTAP variables and coefficients are $qcgds$ (REGINV), $vzwreg$ (VXWREGION), $viwreg$ (VIWREGION) respectively.

¹⁸On a practical level, endogenization of either variable produces very similar results.

¹⁹A uniform shock is one that is applied over all dimensions of a variable. For example, a uniform 5% shock to $ao_{j,r}$ entails a 5% shock to all sectors j within region r .

²⁰Same shock to all exports within a region

²¹Consumption drives trade rather than trade driving consumption.

making the “afreg” variable endogenous, channeling economic growth via greater factor productivity which broadly represents total factor productivity.²²

As with the original model [12], labor supply drives the land conversion service. Land supply is therefore also sensitive to the labor primary factor which enables land conversion. In order to better understand this interaction between the land supply elasticities and provision of labor at the regional level, we run a series of model runs over the hindcasting period 1) shocking labor by 100% of the GDP shock (i.e., same shock) with all land supply variants and 2) shocking labor by 25% of the GDP shock with all land supply variants (Table 4). The choice of 25% and 100% labor and capital supply shocks is arbitrary and represents a potential area of elaboration in future research.

Alternative approaches to determining labor supply include shocks calculated from changes in population [e.g., 49], however given the link between labor and land conversion in the current model we elect to use the 25% and 100% heuristic method.²³ Following the sensitivity analysis, a hindcasting run (Model Run 3) is conducted using the baseline land supply elasticity and a mixed approach the labor shocks. Here the a region-specific labor supply shock is employed at either 25% or 100% based on the level which most closely tracked FAOSTAT data for agricultural land area at the end of the dynamic run in 2020.

3. Results

The reference year update (Model Run 1) moved baseline data closer to recently gathered data for the vast majority of regions (Section 3.1) although a more precise realignment with current data in terms of trade was not possible. Our analysis of the impacts of different land supply elasticities (Model Runs 2) coupled with different levels of labor and capital supply revealed that agricultural land expansion was highly sensitive to both labor supply and the land supply parameter. The final hindcasting run (Model Run 3) with varied labor supply shocks successfully demonstrated the model’s capacity to simulate observed changes in agricultural land use from population and GDP drivers.

3.1. Reference year rebase

The rebasing was generally successful in terms of moving the shocked macro-aggregates (RHS, Equation 2) in-line with collected data however regional investment (rather than trade) absorbed most of the residual GDP shock. Low-income regions in sub-Saharan Africa were the most likely to show disparities between GTAP10a data and World Bank WDI figures (Table 1), with some regions showing up to a 45% discrepancy. Private household and government

²²The current model does not use the standard *afereg* variable for primary factor productivity.

²³It is also not immediately evident that the value of labor within a region will increase proportionally to population growth. Even in the near-term, population growth for many regions peaks which would effectively stifle land conversion if this alternative approach were adopted.

consumption expenditures within these regions were largely brought in-line according to the shocks carried out (Figure 2). Further, adjustments to the

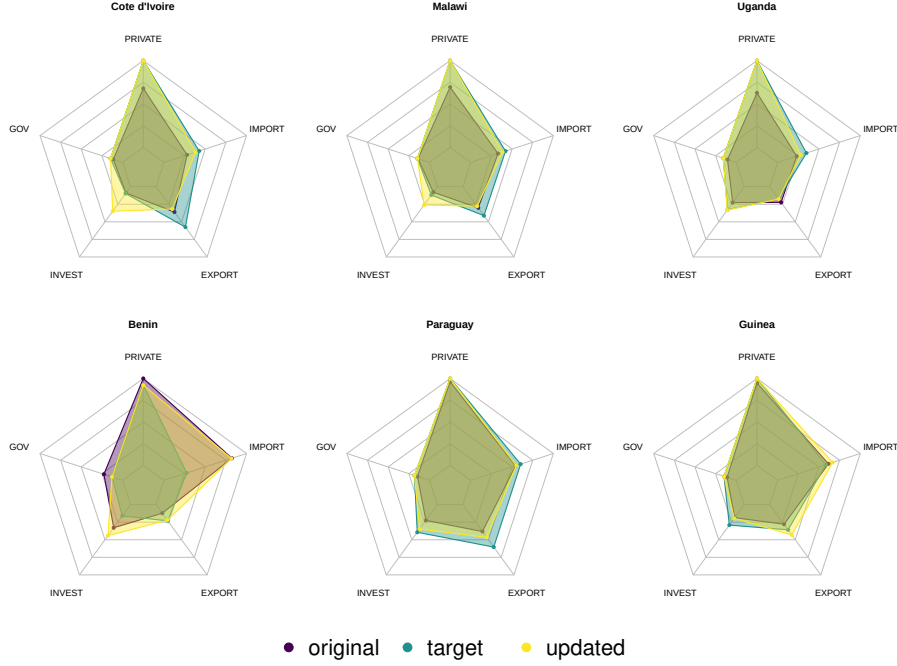


Figure 2: Rebase results for regions where GTAP10a GDP data deviated from collected values by over 30%. Rebase results for all 117 regions are plotted in Section 6.3

mentioned macroaggregates were successful within regions that showed little GDP deviation however varied in terms of underlying expenditures (e.g., Panama, Latvia, and Malta; see Appendix 6.3). The largest persistent deviation was observed across regional investment and trade (see e.g., Iran and Rest of Eastern Africa) due to the fact that these data were allowed to adjust endogenously and thus an increase or decrease in GDP not allocated to exogenous components was free to flow between the remaining components.

3.2. Land supply sensitivity analysis and hindcasting run

For most regions and at the global aggregate level, the baseline land supply elasticity coupled with a 25% labor supply shock closely tracked the historical FAOSTAT data in terms of change in agricultural land (Figure 3). For 29 regions however we found that the baseline land supply and 100% labor supply combination performed better (Table 8). In general we find that the current model slightly overshoots observed increases in agricultural land throughout the study period, particularly among high-income countries not experiencing expansions in agricultural land.

Many regions prone to deforestation were well-simulated in the hindcasting run, with model results for Brazil, Indonesia, and the Angola/Democratic

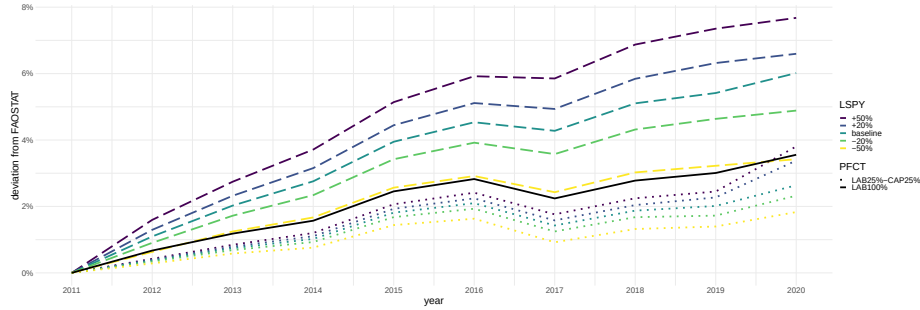


Figure 3: Global deviation of modeled agricultural land from FAOSTAT data by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run (Model Run No. 3).

Republic of Congo region (XAC) all within $\pm 5\%$ of official FAOSTAT data in the year 2020. In terms of regions for which the model poorly tracked observed changes in land-use, 5 regions deviated over 30% in 2020 during the hindcasting run, with the model predicting greater expansion of agricultural land in Ecuador (Figure 151), Uganda (Figure 217), Guinea (Figure 160), and Ethiopia (Figure 155) – indicating the need for caution when interpreting results at the current regional aggregation. Although less common, we also observe the model underpredicting agricultural land expansion in several regions including Venezuela (Figure 221) and Colombia (Figure 144) at -18% and -12% respectively. In the cases of Uganda and Venezuela, there is reason to doubt the accuracy of FAOSTAT data on agricultural land area which remains unchanged during this period.

4. Discussion

Within the current study we modify the 2011 reference year such that it more closely resembles the most recent economic data. We then perform multiple model runs (Table 4) to better understand how the combination of socioeconomic change, land supply elasticities, and labor supply shocks influence fluctuations in agricultural land area over a 9 year period. With this new understanding, a final calibrated hindcasting run is carried out which serves as evidence of the model’s ability to simulate land-use change given population and GDP drivers. This study was carried out in preparation for long-term simulation of SSP2 through 2100.

We find that the TEEMS model closely tracks observed changes in regional land-use given historical changes in socioeconomic drivers. This finding is of vital importance considering our overarching goal of simulating socioeconomic trajectories and associated land-use change through the 2100 time horizon. At a global level we observe that the deviation between model output and historic change in agricultural area is minor (3.5% in 2020, Figure 3). In select regions, however, larger deviations were present despite model calibration efforts. This

discrepancy was most acute within countries located in Eastern Africa and Northern South America. For example, model results for Ecuador in 2020 show 37% more land taken into agricultural production than official FAOSTAT data which shows a decrease from 7.3 million ha in 2011 to 5.4 million ha in 2020. During this period Ecuadorian GDP increased from 86 billion USD to 93 billion in 2020, peaking at over 100 billion in 2018.

This “poor” performing region is worth examining in greater detail to provide a better understanding of how the TEEMS model produces land-use outputs according to socioeconomic changes. Key land-use data and parameters for Ecuador are largely consistent with those of nearby countries. The land supply elasticity for Ecuador (0.054) is lower than that of Colombia (0.065) and Peru: (0.14), indicating a lower propensity to bring unmanaged land into agriculture. The second key component of the land supply function is the asymptote, which was calculated from the same proportion used by other South American regions that are not Brazil [see Table 3, 41]. Given the absence of any distinct differences, it is unlikely that either of these components are responsible for overshooting agricultural expansion in Ecuador. A closer look however reveals that Ecuador has experienced some of the highest rates of deforestation in the region throughout the study period [50]. This leads us to believe that the simplest explanation for this discrepancy is either that recent agricultural land area data from FAOSTAT may be inaccurate or deforested land is not entering agricultural production (i.e., it is deforested and subsequently abandoned).

The absence of an obvious interpretation underscores the importance of clearly delineating between land-use and land cover classes which remains problematic within the context of CGE models where land-use and land cover can be easily conflated. In the case of the current model, economic growth coupled with a higher than average land supply elasticity and land available to come into management (i.e., asymptote) will result in an increase in agricultural land. The TEEMS model does not track flows of marginal land or currently run on a spatial scale capable of identifying subnational land related attributes that would influence agricultural extensification. In future work this may be mitigated by bringing in the agroecological zones (AEZs) and calculating an AEZ-specific asymptote which would serve as an additional check on land entering production.

The rebasing of the 2011 reference year was largely successful and where economic data is available the current methodology could be applied to rebase existing GTAP reference years (2007, 2011, and 2014 within GTAP10a) to a more recent step such as 2020 or a future time step (e.g., 2050). The latter approach would enable modelers to run static, counterfactual simulations at specific points in the future such as those conducted by Anderson et al. [47]. Here it should be noted that GDP components (Equation 2) that are not specified (made exogenous) are likely to adjust in an unpredictable fashion (within the confines of total specified GDP). This was observed in the case of regional investment (I in Equation 2). Although it would have been possible to guide this component through a swap with the capital goods sector of output augmenting technical

change²⁴, unless this swap was retained throughout the entire hindcasting run we would observe a high degree of inaccurate variables at the subsequent time step (i.e., the initial recursive step following the rebase). This is due to the equilibrium state resulting from an exogenous investment shock reverting back once investment is allowed to freely adjust in the new closure (i.e., endogenous investment).

Some discussion regarding the limitations of reference year rebasing is warranted. Although each reference year can be scaled to macroeconomic aggregates, sectoral detail will still be based on the same regional input-output tables which are often from a single year and in some cases are not recent [51]. This highlights one of the key drawbacks of the GTAP database which is the lack of year-specific sectoral detail which inhibits a closer examination of year-over-year changes in sectoral heterogeneity or time-series analysis. A similar issue was noted in the agricultural land area produced by FAOSTAT, with some regions showing identical values for multiple time steps. Although it is beyond the scope of the current work, considering the efforts necessary to rebase an existing reference year in terms of collecting and harmonizing economic data as well as carrying out model runs, larger modeling teams may be best served by creating their own databases from input-output tables with year-specific data [e.g., 52]. The key challenge here is likely to be harmonizing discrepancies between trade data and macroeconomic data [19].

Throughout this study we developed a degree of confidence in the capacity of the TEEMS model to simulate socioeconomic trajectories. Within the context of long-term simulations, we would expect uncertain parameters such as those associated with land supply to have a pronounced effect as the model becomes increasingly untethered from its initial state. Fortunately, in the case of land supply the potential for long-term run-away land conversion is limited by the asymptote which grows smaller at each time step as more land is pulled into management, requiring progressively larger economic incentives (i.e., higher land rent) to elicit the same degree of conversion. In terms of mitigating the potential for model “drift”, the exogenous GDP specification was successful in guiding region economic trajectories. We did however note several limitations to the current modeling framework.

Although the model successfully solved for population, GDP, and several GDP subcomponents (Table 4), in some cases attempts to apply non-uniform shocks spanning additional sets²⁵ proved impossible. For example, we initially intended to calibrate technology variables for crop productivity²⁶ however the model could not be solved at the current regional resolution with an additional technology shock spanning the two crop sectors. Maintaining acceptable levels

²⁴Variable “aoall”, CGDS subset.

²⁵The variables shocked in this study all have a single “region” set while many model variables contain multiple sets (e.g., region, sector, primary factor).

²⁶Swapping aoall(CROPS_COMM,REG) for qo(CROPS_COMM,REG) and shocking crop production according to FAOSTAT data.

of variable accuracy²⁷ also proved challenging when carrying out larger negative shocks. Here the extrapolated accuracy of variables routinely showed decreases within time steps where large negative shocks were applied such as within the 2019 and to a lesser extent 2018 time step.

Finally, it should be noted that the specific elasticities and labor supply shocks employed here may not be generalizable to other GTAP-based models and we strongly suggest conducting a sensitivity analysis as part of any similar efforts to model land-use outputs with a CGE model. Throughout the course of model formulation, we found that land supply was highly sensitive to the choice of shocked variables, their magnitudes, and the associated closures. Although we do not elaborate on labor supply here, ideally labor (as with land) would be made endogenous within a fully specified model, particularly one used to simulate long-term scenarios. This highlights one of the key challenges to working with large-scale, dynamic CGE models, namely the need for expertise across a wide range of disciplines which individual researchers do not typically possess.

5. Conclusion

This work serve as the proof-of-concept for a new economic land-use model capable of simulating long-term paths of economic growth and associated changes in land-use. The current study highlights the importance of conducting hind-casting runs in order to compare model outputs with the historical record. The considerable degree of data collection and harmonization coupled with a series of dynamic runs across the 2011 to 2020 period allowed us to test this model against the historical record and gain new insight into roles of select parameters and exogenous variable specification. Although any model working at 117 regions is susceptible to poorly specified parameters as well as a litany of unknown uncertainties, we have greater confidence in the current model following the rigorous tests applied here. We hope that this work serves as an example for other teams seeking to reproduce and build upon our work, as we have with others. Given the considerable breadth of CGE modeling, we feel confident that proceeding in a transparent and reproducible fashion will ultimately yield synergies as well as allow these tools to become more useful within the context of policy making.

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²⁷Accuracy here refers to the extrapolated estimates from a multi-step approach to solving a system of linear equations.

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6. Supplementary Information

6.1. Study mappings

Table 5: Regional mappings

country.name	iso3c	GTAP.code	study.name	study.code
Afghanistan	afg	xsa	Rest of South Asia	xsa
Albania	alb	alb	Albania	alb
Algeria	dza	xnf	Rest of North Africa	xnf
American Samoa	asm	xoc	Rest of Oceania	xoc
Andorra	and	xer	Rest of Europe	xer
Angola	ago	xac	South Central Africa	xac
Anguilla	aia	xcb	Caribbean	car
Antarctica	ata	xtw	Rest of the World	xtw_xna
Antigua & Barbuda	atg	xcb	Caribbean	car
Argentina	arg	arg	Argentina	arg
Armenia	arm	arm	The Caucasus	cau
Aruba	abw	xcb	Caribbean	car
Australia	aus	aus	Australia	aus
Austria	aut	aut	Austria	aut
Azerbaijan	aze	aze	The Caucasus	cau

Bahamas	bhs	xcb	Caribbean	car
Bahrain	bhr	bhr	Petrol States	pet
Bangladesh	bgd	bgd	Bangladesh	bgd
Barbados	brb	xcb	Caribbean	car
Belarus	blr	blr	Belarus	blr
Belgium	bel	bel	Belgium	bel
Belize	blz	xca	Rest of Central America	blz_gtm
Benin	ben	ben	Benin	ben
Bermuda	bmu	xna	Rest of the World	xtw_xna
Bhutan	btn	xsa	Rest of South Asia	xsa
Bolivia	bol	bol	Bolivia	bol
Bosnia & Herzegovina	bih	xer	Rest of Europe	xer
Botswana	bwa	bwa	Botswana	bwa
Brazil	bra	bra	Brazil	bra
British Indian Ocean Territory	iot	xtw	Rest of the World	xtw_xna
British Virgin Islands	vgb	xcb	Caribbean	car
Brunei	brn	brn	Malaysia+	brn_mys
Bulgaria	bgr	bgr	Bulgaria	bgr
Burkina Faso	bfa	bfa	Burkina Faso	bfa
Burundi	bdi	xec	Rest of Eastern Africa	xec
Cambodia	khm	khm	Rest of Southeast Asia	xse
Cameroon	cmr	cmr	Cameroon	cmr
Canada	can	can	Canada	can
Cape Verde	cpv	xwf	Rest of Western Africa	mar_xwf
Cayman Islands	cym	xcb	Caribbean	car
Central African Republic	caf	xcf	Central Africa	xcf
Chad	tcd	xcf	Central Africa	xcf
Channel Islands	chi	xer	Rest of Europe	xer
Chile	chl	chl	Chile	chl
China	chn	chn	China	chn
Colombia	col	col	Colombia	col
Comoros	com	xec	Rest of Eastern Africa	xec
Congo - Brazzaville	cog	xcf	Central Africa	xcf
Congo - Kinshasa	cod	xac	South Central Africa	xac
Cook Islands	cok	xoc	Rest of Oceania	xoc
Costa Rica	cri	cri	Costa Rica	cri
Côte d'Ivoire	civ	civ	Cote d'Ivoire	civ
Croatia	hrv	hrv	Croatia	hrv
Cuba	cub	xcb	Caribbean	car
Cyprus	cyp	cyp	Cyprus	cyp
Czechia	cze	cze	Czech Republic	cze
Denmark	dnk	dnk	Denmark	dnk
Djibouti	dji	xec	Rest of Eastern Africa	xec
Dominica	dma	xcb	Caribbean	car
Dominican Republic	dom	dom	Caribbean	car
Ecuador	ecu	ecu	Ecuador	ecu
Egypt	egy	egy	Egypt	egy
El Salvador	slv	slv	El Salvador	slv
Equatorial Guinea	gnq	xcf	Central Africa	xcf
Eritrea	eri	xec	Rest of Eastern Africa	xec
Estonia	est	est	Estonia	est
Eswatini	swz	xsc	South Africa+	zaf
Ethiopia	eth	eth	Ethiopia	eth
Falkland Islands	flk	xsm	Caribbean	car
Faroe Islands	fro	xer	Rest of Europe	xer

Fiji	fji	xoc	Rest of Oceania	xoc
Finland	fin	fin	Finland	fin
France	fra	fra	France	fra
French Guiana	guf	xsm	Caribbean	car
French Polynesia	pyf	xoc	Rest of Oceania	xoc
French Southern Territories	atf	xtw	Rest of the World	xtw_xna
Gabon	gab	xcf	Central Africa	xcf
Gambia	gmb	xwf	Rest of Western Africa	mar_xwf
Georgia	geo	geo	The Caucasus	cau
Germany	deu	deu	Germany	deu
Ghana	gha	gha	Ghana	gha
Gibraltar	gib	xer	Rest of Europe	xer
Greece	grc	grc	Greece	grc
Greenland	grl	xna	Rest of the World	xtw_xna
Grenada	grd	xcb	Caribbean	car
Guadeloupe	glp	fra	France	fra
Guam	gum	xoc	Rest of Oceania	xoc
Guatemala	gtm	gtm	Rest of Central America	blz_gtm
Guinea	gin	gin	Guinea	gin
Guinea-Bissau	gnb	xwf	Rest of Western Africa	mar_xwf
Guyana	guy	xsm	Caribbean	car
Haiti	hti	xcb	Caribbean	car
Honduras	hnd	hnd	Honduras	hnd
Hong Kong SAR China	hkg	hkg	Rest of East Asia	eAsia
Hungary	hun	hun	Hungary	hun
Iceland	isl	xef	Rest of EFTA	nor_xef
India	ind	ind	India	ind
Indonesia	idn	idn	Indonesia	idn
Iran	irn	irn	Iran Islamic Republic of	irn
Iraq	irq	xws	Rest of Western Asia	xws
Ireland	irl	irl	Ireland	irl
Isle of Man	imn	xer	Rest of Europe	xer
Israel	isr	isr	Israel	isr
Italy	ita	ita	Italy	ita
Jamaica	jam	jam	Caribbean	car
Japan	jpn	jpn	Japan	jpn
Jordan	jor	jor	Jordan	jor
Kazakhstan	kaz	kaz	Kazakhstan	kaz
Kenya	ken	ken	Kenya	ken
Kiribati	kir	xoc	Rest of Oceania	xoc
Kuwait	kwt	kwt	Kuwait	kwt
Kyrgyzstan	kgz	kgz	Rest of Central Asia	xsu
Laos	lao	lao	Rest of Southeast Asia	xse
Latvia	lva	lva	Latvia	lva
Lebanon	lbn	xws	Rest of Western Asia	xws
Lesotho	lso	xsc	South Africa+	zaf
Liberia	lbr	xwf	Rest of Western Africa	mar_xwf
Libya	lby	xnf	Rest of North Africa	xnf
Liechtenstein	lie	xef	Rest of EFTA	nor_xef
Lithuania	ltu	ltu	Lithuania	ltu
Luxembourg	lux	lux	Luxembourg	lux
Macao SAR China	mac	xea	Rest of East Asia	eAsia
Madagascar	mdg	mdg	Madagascar	mdg
Malawi	mwi	mwi	Malawi	mwi
Malaysia	mys	mys	Malaysia+	brn_mys

Maldives	mdv	xsa	Rest of South Asia	xsa
Mali	mli	xwf	Rest of Western Africa	mar_xwf
Malta	mlt	mlt	Malta	mlt
Marshall Islands	mhl	xoc	Rest of Oceania	xoc
Martinique	mtq	fra	France	fra
Mauritania	mrt	xwf	Rest of Western Africa	mar_xwf
Mauritius	mus	mus	Mauritius	mus
Mayotte	myt	xec	Rest of Eastern Africa	xec
Mexico	mex	mex	Mexico	mex
Micronesia (Federated States of)	fsm	xoc	Rest of Oceania	xoc
Moldova	mda	xee	Rest of Eastern Europe	xee
Monaco	mco	xer	Rest of Europe	xer
Mongolia	mng	mng	Rest of East Asia	eAsia
Montenegro	mne	xer	Rest of Europe	xer
Montserrat	msr	xcb	Caribbean	car
Morocco	mar	mar	Rest of Western Africa	mar_xwf
Mozambique	moz	moz	Mozambique	moz
Myanmar (Burma)	mmr	xse	Rest of Southeast Asia	xse
Namibia	nam	nam	Namibia	nam
Nauru	nru	xoc	Rest of Oceania	xoc
Nepal	npl	npl	Rest of South Asia	xsa
Netherlands	nld	nld	Netherlands	nld
New Caledonia	ncl	xoc	Rest of Oceania	xoc
New Zealand	nzl	nzl	New Zealand	nzl
Nicaragua	nic	nic	Nicaragua	nic
Niger	ner	xwf	Rest of Western Africa	mar_xwf
Nigeria	nga	nga	Nigeria	nga
Niue	niu	xoc	Rest of Oceania	xoc
North Korea	prk	xea	Rest of East Asia	eAsia
North Macedonia	mkd	xer	Rest of Europe	xer
Northern Mariana Islands	mnp	xoc	Rest of Oceania	xoc
Norway	nor	nor	Rest of EFTA	nor_xef
Oman	omn	omn	Rest of Western Asia	xws
Pakistan	pak	pak	Pakistan	pak
Palau	plw	xoc	Rest of Oceania	xoc
Palestinian Territories	pse	xws	Rest of Western Asia	xws
Panama	pan	pan	Panama	pan
Papua New Guinea	png	xoc	Rest of Oceania	xoc
Paraguay	pry	pry	Paraguay	pry
Peru	per	per	Peru	per
Philippines	phl	phl	Philippines	phl
Poland	pol	pol	Poland	pol
Portugal	prt	prt	Portugal	prt
Puerto Rico	pri	pri	Puerto Rico	usa
Qatar	qat	qat	Petrol States	pet
Réunion	reu	fra	France	fra
Romania	rou	rou	Romania	rou
Russia	rus	rus	Russian Federation	rus
Rwanda	rwa	rwa	Rwanda	rwa
Samoa	wsm	xoc	Rest of Oceania	xoc
San Marino	smr	xer	Rest of Europe	xer
São Tomé & Príncipe	stp	xcf	Central Africa	xcf
Saudi Arabia	sau	sau	Saudi Arabia	sau
Senegal	sen	sen	Senegal	sen
Serbia	srb	xer	Rest of Europe	xer

Seychelles	syc	xec	Rest of Eastern Africa	xec
Sierra Leone	sle	xwf	Rest of Western Africa	mar_xwf
Singapore	sgp	sgp	Singapore	sgp
Slovakia	svk	svk	Slovakia	svk
Slovenia	svn	svn	Slovenia	svn
Solomon Islands	slb	xoc	Rest of Oceania	xoc
Somalia	som	xec	Rest of Eastern Africa	xec
South Africa	zaf	zaf	South Africa+	zaf
South Korea	kor	kor	Korea	kor
Spain	esp	esp	Spain	esp
Sri Lanka	lka	lka	Rest of South Asia	xsa
St. Helena	shn	xwf	Rest of Western Africa	mar_xwf
St. Kitts & Nevis	kna	xcb	Caribbean	car
St. Lucia	lca	xcb	Caribbean	car
St. Pierre & Miquelon	spm	xna	Rest of the World	xtw_xna
St. Vincent & Grenadines	vct	xcb	Caribbean	car
Sudan	sdn	xec	Rest of Eastern Africa	xec
Suriname	sur	xsm	Caribbean	car
Sweden	swe	swe	Sweden	swe
Switzerland	che	che	Switzerland	che
Syria	syr	xws	Rest of Western Asia	xws
Taiwan	twm	twm	Taiwan	twm
Tajikistan	tjk	tjk	Rest of Central Asia	xsu
Tanzania	tza	tza	Tanzania	tza
Thailand	tha	tha	Thailand	tha
Timor-Leste	tls	xse	Rest of Southeast Asia	xse
Togo	tgo	tgo	Togo	tgo
Tokelau	tkl	xoc	Rest of Oceania	xoc
Tonga	ton	xoc	Rest of Oceania	xoc
Trinidad & Tobago	tto	tto	Caribbean	car
Tunisia	tun	tun	Tunisia	tun
Turkey	tur	tur	Turkey	tur
Turkmenistan	tkm	xsu	Rest of Central Asia	xsu
Turks & Caicos Islands	tca	xcb	Caribbean	car
Tuvalu	tuv	xoc	Rest of Oceania	xoc
U.S. Virgin Islands	vir	xcb	Caribbean	car
Uganda	uga	uga	Uganda	uga
Ukraine	ukr	ukr	Ukraine	ukr
United Arab Emirates	are	are	Petrol States	pet
United Kingdom	gbr	gbr	United Kingdom	gbr
United States	usa	usa	United States of America	usa
Uruguay	ury	ury	Uruguay	ury
Uzbekistan	uzb	xsu	Rest of Central Asia	xsu
Vanuatu	vut	xoc	Rest of Oceania	xoc
Vatican City	vat	xer	Rest of Europe	xer
Venezuela	ven	ven	Venezuela	ven
Vietnam	vnm	vnm	Viet Nam	vnm
Wallis & Futuna	wlf	xoc	Rest of Oceania	xoc
Western Sahara	esh	xnf	Rest of North Africa	xnf
Yemen	yem	xws	Rest of Western Asia	xws
Zambia	zmb	zmb	Zambia	zmb
Zimbabwe	zwe	zwe	Zimbabwe	zwe

Table 6: Sector mappings

GTAP.code	GTAP.name	study.code	study.name
afs	accommodation, food and service activities	svces	services
atp	air transport	svces	services
b_t	beverages and tobacco products	food	food
bph	basic pharmaceutical products	mnfcs	manufacturing
c_b	sugar cane, sugar beet	c_four	C ₄ fixation crop
chm	chemical products	mnfcs	manufacturing
cmn	communication	svces	services
cmt	bovine meat products	food	food
cns	construction	svces	services
coa	coal	mnfcs	manufacturing
ctl	bovine cattle, sheep and goats, horses	livestock	ruminants+dairy
dwe	dwellings	svces	services
edu	education	svces	services
eeq	electrical equipment	mnfcs	manufacturing
ele	computer, electronic and optical products	mnfcs	manufacturing
ely	electricity	mnfcs	manufacturing
fmp	metal products	mnfcs	manufacturing
frs	forestry	frs	forestry
fsh	fishing	food	food
gas	gas	mnfcs	manufacturing
gdt	gas manufacture, distribution	mnfcs	manufacturing
gro	cereal grains nec	c_four	C ₄ fixation crop
hht	human health and social work activities	svces	services
i_s	ferrous metals	mnfcs	manufacturing
ins	insurance	svces	services
lea	leather products	mnfcs	manufacturing
lum	wood products	mnfcs	manufacturing
mil	dairy products	food	food
mvh	motor vehicles and parts	mnfcs	manufacturing
nfm	metals nec	mnfcs	manufacturing
nmn	mineral products nec	mnfcs	manufacturing
oap	animal products nec	food	food
obs	business services nec	svces	services
ocr	crops nec	c_three	C ₃ fixation crop
ofd	food products nec	food	food
ofi	financial services nec	svces	services
oil	oil	mnfcs	manufacturing
ome	machinery and equipment nec	mnfcs	manufacturing
omf	manufactures nec	mnfcs	manufacturing
omt	meat products nec	food	food
osd	oil seeds	c_three	C ₃ fixation crop
osg	public administration and defense	svces	services
otn	transport equipment nec	mnfcs	manufacturing
otp	transport nec	svces	services
oxt	minerals nec	mnfcs	manufacturing
p_c	petroleum, coal products	mnfcs	manufacturing
pcr	processed rice	food	food
pdr	paddy rice	c_three	C ₃ fixation crop
pfb	plant-based fibers	c_three	C ₃ fixation crop
ppp	paper products, publishing	mnfcs	manufacturing
rmk	raw milk	livestock	ruminants+dairy

ros	recreational and other services	svces	services
rpp	rubber and plastic products	mnfcs	manufacturing
rsa	real estate activities	svces	services
sgr	sugar	food	food
tex	textiles	mnfcs	manufacturing
trd	trade	svces	services
v_f	vegetables, fruit, nuts	c_three	C ₃ fixation crop
vol	vegetable oils and fats	food	food
wap	wearing apparel	mnfcs	manufacturing
whs	warehousing and support activities	svces	services
wht	wheat	c_three	C ₃ fixation crop
wol	wool, silk-worm cocoons	livestock	ruminants+dairy
wtp	water transport	svces	services
wtr	water	svces	services
cgds	capital goods commodities	zCGDS	capital goods commodities

Table 7: GTAP crop to FAO CPC mappings

GTAP.code	GTAP.name	item.name	CPC.code
c_b	sugar cane, sugar beet	Sugar beet	'01801
c_b	sugar cane, sugar beet	Sugar cane	'01802
c_b	sugar cane, sugar beet	Other sugar crops n.e.c.	'01809
gro	cereal grains nec	Barley	'0115
gro	cereal grains nec	Maize (corn)	'0112
gro	cereal grains nec	Millet	'0118
gro	cereal grains nec	Oats	'0117
gro	cereal grains nec	Rye	'0116
gro	cereal grains nec	Sorghum	'0114
gro	cereal grains nec	Triticale	'01191
gro	cereal grains nec	Canary seed	'01195
gro	cereal grains nec	Cereals n.e.c.	'01199.90
gro	cereal grains nec	Buckwheat	'01192
gro	cereal grains nec	Mixed grain	'01199.02
gro	cereal grains nec	Fonio	'01193
gro	cereal grains nec	Quinoa	'01194
ocr	crops nec	Anise, badian, coriander...	'01654
ocr	crops nec	Other stimulant...	'01699
ocr	crops nec	Hop cones	'01659
ocr	crops nec	Unmanufactured tobacco	'01970
ocr	crops nec	Chillies and peppers...	'01652
ocr	crops nec	Cocoa beans	'01640
ocr	crops nec	Coffee, green	'01610
ocr	crops nec	Mat<e leaves	'01630
ocr	crops nec	Tea leaves	'01620
ocr	crops nec	Ginger, raw	'01657
ocr	crops nec	Natural rubber in primary forms	'01950.01
ocr	crops nec	Chicory roots	'01691
ocr	crops nec	Vanilla, raw	'01658
ocr	crops nec	Pepper (Piper spp.), raw	'01651
ocr	crops nec	Nutmeg, mace, cardamoms, raw	'01653
ocr	crops nec	Pyrethrum, dried flowers	'01930.02
ocr	crops nec	Peppermint, spearmint	'01930.01
ocr	crops nec	Cinnamon and cinnamon-tree flowers, raw	'01655
ocr	crops nec	Cloves (whole stems), raw	'01656
osd	oil seeds	Linseed	'01441
osd	oil seeds	Olives	'01450
osd	oil seeds	Sesame seed	'01444
osd	oil seeds	Sunflower seed	'01445
osd	oil seeds	Soya beans	'0141
osd	oil seeds	Groundnuts, excluding shelled	'0142
osd	oil seeds	Rape or colza seed	'01443
osd	oil seeds	Castor oil seeds	'01447
osd	oil seeds	Oil palm fruit	'01491.01
osd	oil seeds	Safflower seed	'01446
osd	oil seeds	Tung nuts	'01499.02
osd	oil seeds	Mustard seed	'01442
osd	oil seeds	Other oil seeds, n.e.c.	'01449.90
osd	oil seeds	Poppy seed	'01448
osd	oil seeds	Coconuts, in shell	'01460
osd	oil seeds	Karite nuts (sheanuts)	'01499.01

osd	oil seeds	Melonseed	'01449.01
osd	oil seeds	Hempseed	'01449.02
osd	oil seeds	Tallowtree seeds	'01499.04
osd	oil seeds	Kapok fruit	'01499.05
osd	oil seeds	Jojoba seeds	'01499.03
pdr	paddy rice	Rice	'0113
pfb	plant-based fibers	Seed cotton, unginned	'01921.01
pfb	plant-based fibers	Kenaf, and other textile bast fibres...	'01922.02
pfb	plant-based fibers	Sisal, raw	'01929.05
pfb	plant-based fibers	Other fibre crops, raw, n.e.c.	'01929.90
pfb	plant-based fibers	True hemp, raw or retted	'01929.02
pfb	plant-based fibers	Coir, raw	'01929.08
pfb	plant-based fibers	Jute, raw or retted	'01922.01
pfb	plant-based fibers	Ramie, raw or retted	'01929.04
pfb	plant-based fibers	Agave fibres, raw, n.e.c.	'01929.06
pfb	plant-based fibers	Abaca, manila hemp, raw	'01929.07
v_f	vegetables, fruit, nuts	Almonds, in shell	'01371
v_f	vegetables, fruit, nuts	Apples	'01341
v_f	vegetables, fruit, nuts	Apricots	'01343
v_f	vegetables, fruit, nuts	Cantaloupes and other melons	'01229
v_f	vegetables, fruit, nuts	Figs	'01315
v_f	vegetables, fruit, nuts	Grapes	'01330
v_f	vegetables, fruit, nuts	Onions and shallots, dry...	'01253.02
v_f	vegetables, fruit, nuts	Oranges	'01323
v_f	vegetables, fruit, nuts	Other berries and fruits...	'01355.90
v_f	vegetables, fruit, nuts	Other citrus fruit, n.e.c.	'01329
v_f	vegetables, fruit, nuts	Other fruits, n.e.c.	'01359.90
v_f	vegetables, fruit, nuts	Other nuts...	'01379.90
v_f	vegetables, fruit, nuts	Other pulses n.e.c.	'01709.90
v_f	vegetables, fruit, nuts	Other stone fruits	'01349.20
v_f	vegetables, fruit, nuts	Other vegetables, fresh n.e.c.	'01290.90
v_f	vegetables, fruit, nuts	Peaches and nectarines	'01345
v_f	vegetables, fruit, nuts	Pears	'01342.01
v_f	vegetables, fruit, nuts	Pistachios, in shell	'01375
v_f	vegetables, fruit, nuts	Plums and sloes	'01346
v_f	vegetables, fruit, nuts	Potatoes	'01510
v_f	vegetables, fruit, nuts	Walnuts, in shell	'01376
v_f	vegetables, fruit, nuts	Watermelons	'01221
v_f	vegetables, fruit, nuts	Beans, dry	'01701
v_f	vegetables, fruit, nuts	Broad beans and horse beans, dry	'01702
v_f	vegetables, fruit, nuts	Broad beans and horse beans, green	'01243
v_f	vegetables, fruit, nuts	Cabbages	'01212
v_f	vegetables, fruit, nuts	Carrots and turnips	'01251
v_f	vegetables, fruit, nuts	Cauliflowers and broccoli	'01213
v_f	vegetables, fruit, nuts	Cherries	'01344.02
v_f	vegetables, fruit, nuts	Chestnuts, in shell	'01373
v_f	vegetables, fruit, nuts	Chillies and peppers...	'01231
v_f	vegetables, fruit, nuts	Cucumbers and gherkins	'01232
v_f	vegetables, fruit, nuts	Dates	'01314
v_f	vegetables, fruit, nuts	Eggplants (aubergines)	'01233
v_f	vegetables, fruit, nuts	Green garlic	'01252
v_f	vegetables, fruit, nuts	Leeks and other alliaceous vegetables	'01254
v_f	vegetables, fruit, nuts	Lemons and limes	'01322
v_f	vegetables, fruit, nuts	Lettuce and chicory	'01214
v_f	vegetables, fruit, nuts	Mushrooms and truffles	'01270

v_f	vegetables, fruit, nuts	Okra	'01239.01
v_f	vegetables, fruit, nuts	Onions and shallots, green	'01253.01
v_f	vegetables, fruit, nuts	Other beans, green	'01241.90
v_f	vegetables, fruit, nuts	Peas, green	'01242
v_f	vegetables, fruit, nuts	Pumpkins, squash and gourds	'01235
v_f	vegetables, fruit, nuts	Quinces	'01342.02
v_f	vegetables, fruit, nuts	Sour cherries	'01344.01
v_f	vegetables, fruit, nuts	Spinach	'01215
v_f	vegetables, fruit, nuts	Strawberries	'01354
v_f	vegetables, fruit, nuts	Tangerines, mandarins, clementines	'01324
v_f	vegetables, fruit, nuts	Tomatoes	'01234
v_f	vegetables, fruit, nuts	Vetches	'01709.01
v_f	vegetables, fruit, nuts	Artichokes	'01216
v_f	vegetables, fruit, nuts	Bananas	'01312
v_f	vegetables, fruit, nuts	Chick peas, dry	'01703
v_f	vegetables, fruit, nuts	Lentils, dry	'01704
v_f	vegetables, fruit, nuts	Locust beans (carobs)	'01356
v_f	vegetables, fruit, nuts	Other tropical fruits, n.e.c.	'01319
v_f	vegetables, fruit, nuts	Peas, dry	'01705
v_f	vegetables, fruit, nuts	Pomelos and grapefruits	'01321
v_f	vegetables, fruit, nuts	Cashew nuts, in shell	'01372
v_f	vegetables, fruit, nuts	Cassava, fresh	'01520.01
v_f	vegetables, fruit, nuts	Pineapples	'01318
v_f	vegetables, fruit, nuts	Sweet potatoes	'01530
v_f	vegetables, fruit, nuts	Mangoes, guavas and mangosteens	'01316
v_f	vegetables, fruit, nuts	Taro	'01550
v_f	vegetables, fruit, nuts	Yams	'01540
v_f	vegetables, fruit, nuts	Asparagus	'01211
v_f	vegetables, fruit, nuts	Avocados	'01311
v_f	vegetables, fruit, nuts	Lupins	'01709.02
v_f	vegetables, fruit, nuts	Papayas	'01317
v_f	vegetables, fruit, nuts	String beans	'01241.01
v_f	vegetables, fruit, nuts	Hazelnuts, in shell	'01374
v_f	vegetables, fruit, nuts	Blueberries	'01355.01
v_f	vegetables, fruit, nuts	Cow peas, dry	'01706
v_f	vegetables, fruit, nuts	Currants	'01351.01
v_f	vegetables, fruit, nuts	Green corn (maize)	'01290.01
v_f	vegetables, fruit, nuts	Kiwi fruit	'01352
v_f	vegetables, fruit, nuts	Persimmons	'01359.01
v_f	vegetables, fruit, nuts	Raspberries	'01353.01
v_f	vegetables, fruit, nuts	Gooseberries	'01351.02
v_f	vegetables, fruit, nuts	Cranberries	'01355.02
v_f	vegetables, fruit, nuts	Pigeon peas, dry	'01707
v_f	vegetables, fruit, nuts	Plantains and cooking bananas	'01313
v_f	vegetables, fruit, nuts	Areca nuts	'01379.01
v_f	vegetables, fruit, nuts	Other pome fruits	'01349.10
v_f	vegetables, fruit, nuts	Edible roots and tubers...	'01599.10
v_f	vegetables, fruit, nuts	Yautia	'01591
v_f	vegetables, fruit, nuts	Kola nuts	'01379.02
v_f	vegetables, fruit, nuts	Cashewapple	'01359.02
v_f	vegetables, fruit, nuts	Cassava leaves	'01219.01
v_f	vegetables, fruit, nuts	Bambara beans, dry	'01708
v_f	vegetables, fruit, nuts	Brazil nuts, in shell	'01377
wht	wheat	Wheat	'0111

6.2. Parameter aggregation methodology

See Table 3 for parameter and coefficient names and descriptions as well as set indices. Hat ($\hat{\cdot}$) indicates the new parameter value while asterisk (*) indicates the destination set mapping.

$$\hat{\sigma}_{D_i} = \frac{\sum_i^{i^*} (\sigma_{D_i} \sum_r (vdpa_{i,r} + vdga_{i,r} + vdfa_{i,r} + vipa_{i,r} + viga_{i,r} + vifa_{i,r}))}{\sum_{i,r}^{i^*} (vdpa_{i,r} + vdga_{i,r} + vdfa_{i,r} + vipa_{i,r} + viga_{i,r} + vifa_{i,r})} \quad (3)$$

$$\hat{\sigma}_{M_i} = \frac{\sum_i^{i^*} (\sigma_{M_i} \sum_r (vipa_{i,r} + viga_{i,r} + vifa_{i,r}))}{\sum_{i,r}^{i^*} (vipa_{i,r} + viga_{i,r} + vifa_{i,r})} \quad (4)$$

$$\hat{\sigma}_{VA_j} = \begin{cases} \sigma_{VA_j} \neq cgds & \frac{\sum_j^{j^*} (\sigma_{VA_j} \sum_r (evfa_{j,r}))}{\sum_{j,r}^{j^*} (evfa_{j,r})} \\ \sigma_{VA_j} = cgds & \sigma_{VA_j} \end{cases} \quad (5)$$

$$\hat{\eta}_{i,r} = \frac{\sum_{i,r}^{i^* r^*} \eta_{i,r} \sum_{i,r} (tons_{i,j,r})}{\sum_{i,r}^{i^* r^*} (tons_{i,j,r})} \quad (6)$$

$$\hat{\theta}_r = \frac{\sum_r^{r^*} \theta_r \sum_r (lcov_{i,j=cropland,r})}{\sum_r^{r^*} (lcov_{i,j=cropland,r})} \quad (7)$$

$$\hat{\gamma}_{i,r} = \frac{\sum_{i,r}^{i^* r^*} \gamma_{i,r} \sum_{i,r} (vdpa_{i,r} + vipa_{i,r})}{\sum_{i,r}^{i^* r^*} (vdpa_{i,r} + vipa_{i,r})} \quad (8)$$

$$\hat{\beta}_{i,r} = \frac{\sum_{i,r}^{i^* r^*} (\beta_{i,r} \sum_{i,r} (vdpa_{i,r} + vipa_{i,r}))}{\sum_{i,r}^{i^* r^*} (vdpa_{i,r} + vipa_{i,r})} \quad (9)$$

6.3. 2011 Reference year update: all regions

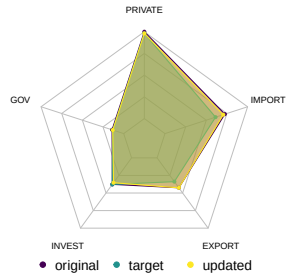


Figure 4: Albania rebase.

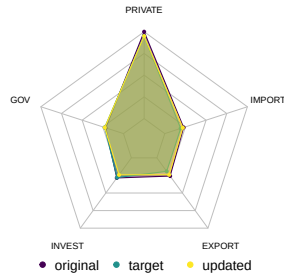


Figure 5: Argentina rebase.

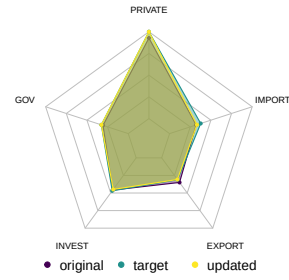


Figure 6: Australia rebase.

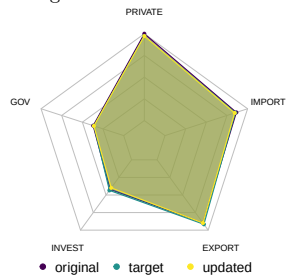


Figure 7: Austria rebase.

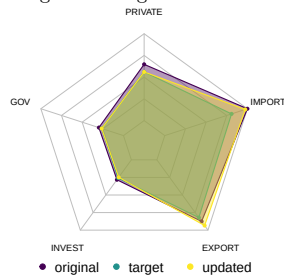


Figure 8: Belgium rebase.

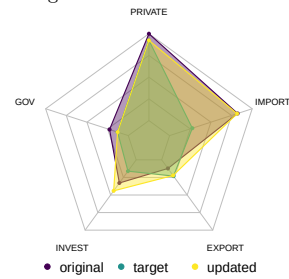


Figure 9: Benin rebase.

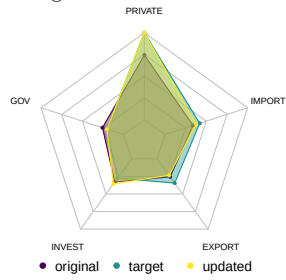


Figure 10: Burkina Faso rebase.

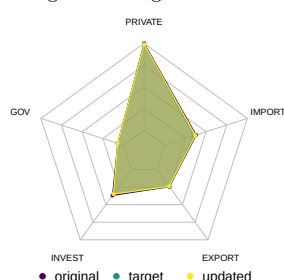


Figure 11: Bangladesh rebase.

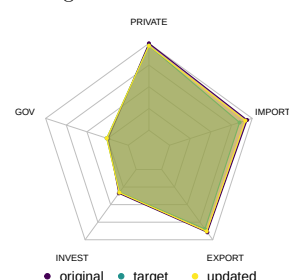


Figure 12: Bulgaria rebase.

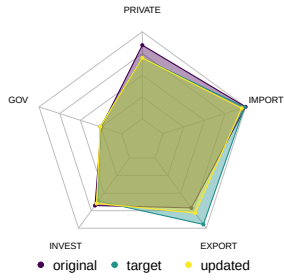


Figure 13: Belarus rebase.

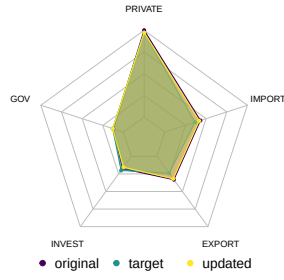


Figure 14: Rest of Central America rebase.

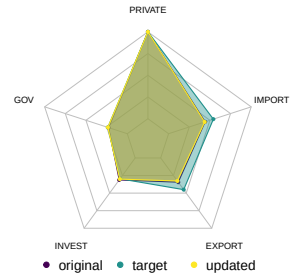


Figure 15: Bolivia rebase.

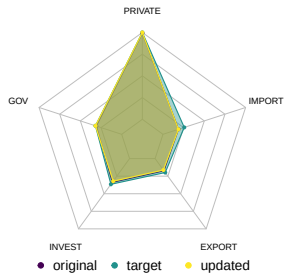


Figure 16: Brazil rebase.

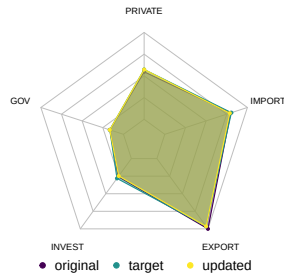


Figure 17: Malaysia+ rebase.

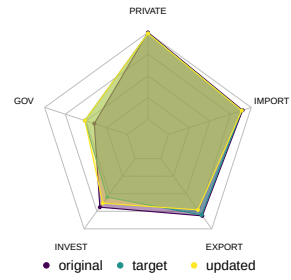


Figure 18: Botswana rebase.

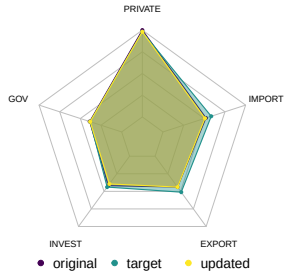


Figure 19: Canada rebase.

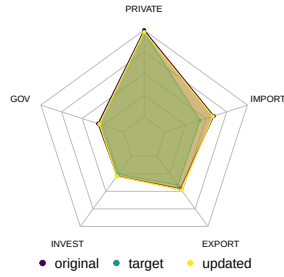


Figure 20: Caribbean rebase.

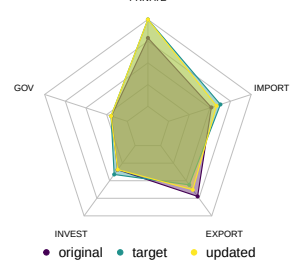


Figure 21: The Caucasus rebase.

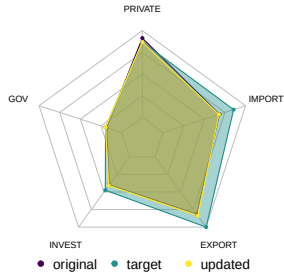


Figure 22: Switzerland rebase.

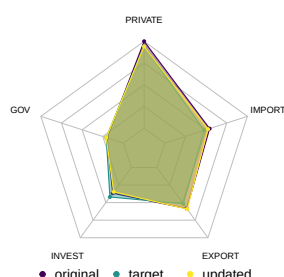


Figure 23: Chile rebase.

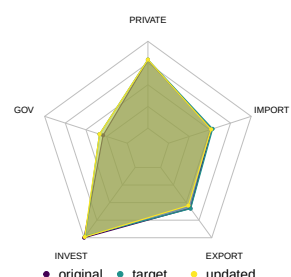


Figure 24: China rebase.

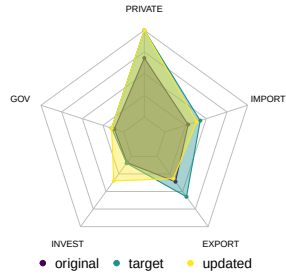


Figure 25: Cote d'Ivoire rebase.

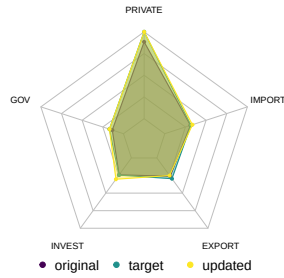


Figure 26: Cameroon rebase.

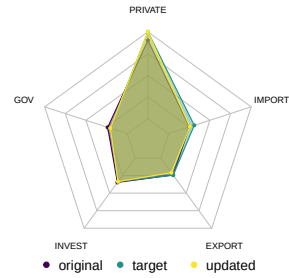


Figure 27: Colombia rebase.

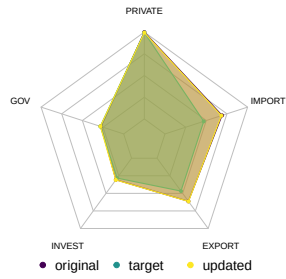


Figure 28: Costa Rica rebase.

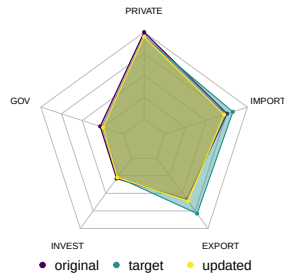


Figure 29: Cyprus rebase.

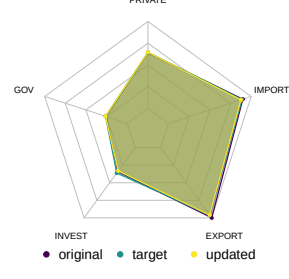


Figure 30: Czech Republic rebase.

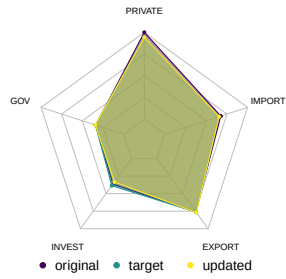


Figure 31: Germany rebase.

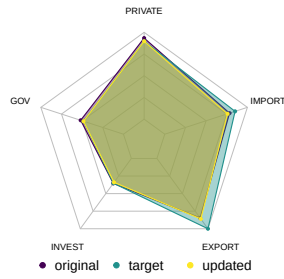


Figure 32: Denmark rebase.

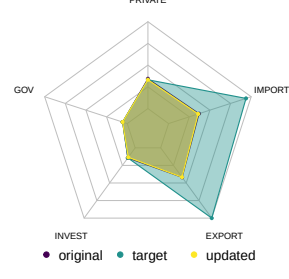


Figure 33: Rest of East Asia rebase.

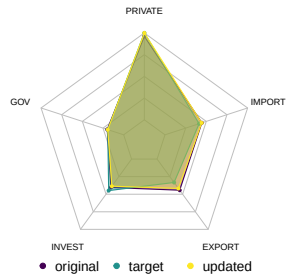


Figure 34: Ecuador rebase.

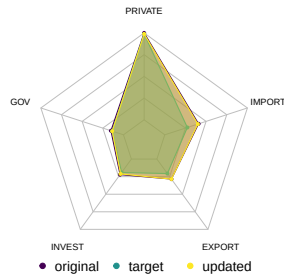


Figure 35: Egypt rebase.

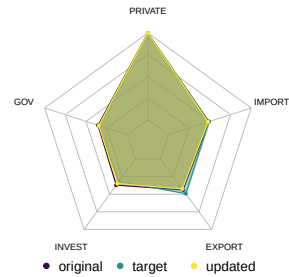


Figure 36: Spain rebase.

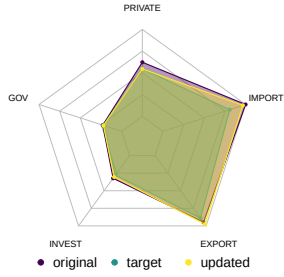


Figure 37: Estonia rebase.

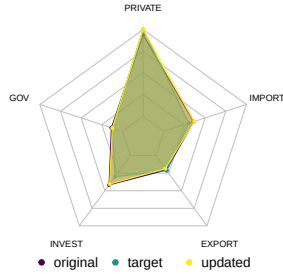


Figure 38: Ethiopia rebase.

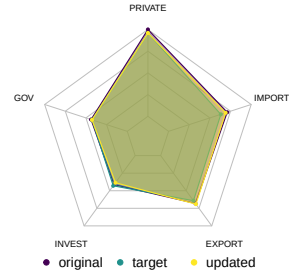


Figure 39: Finland rebase.

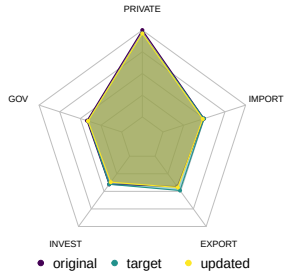


Figure 40: France rebase.

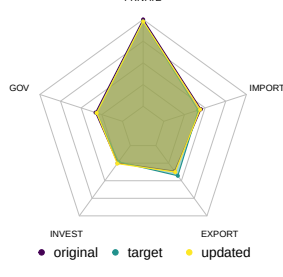


Figure 41: United Kingdom rebase.

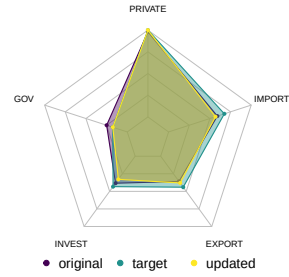


Figure 42: Ghana rebase.

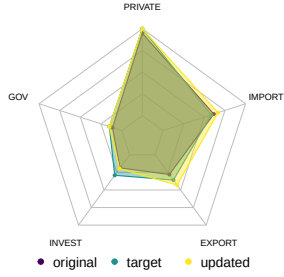


Figure 43: Guinea rebase.

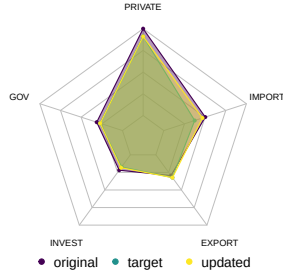


Figure 44: Greece rebase.

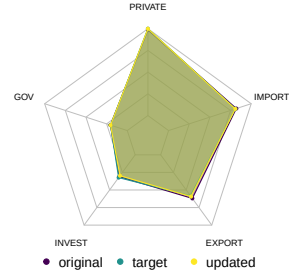


Figure 45: Honduras rebase.

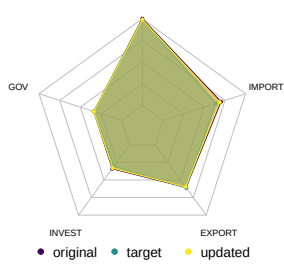


Figure 46: Croatia rebase.

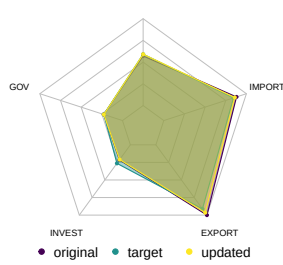


Figure 47: Hungary rebase.

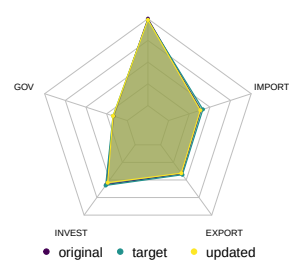


Figure 48: Indonesia rebase.

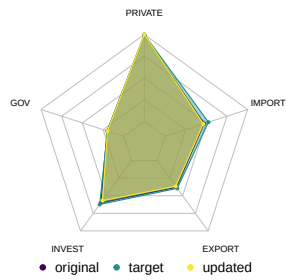


Figure 49: India rebase.

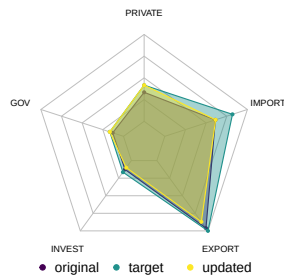


Figure 50: Ireland rebase.

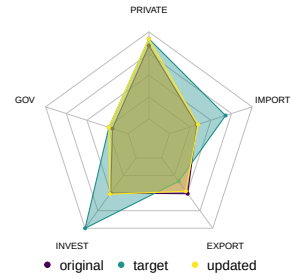


Figure 51: Iran Islamic Republic of rebase.

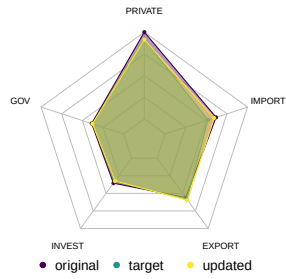


Figure 52: Israel rebase.

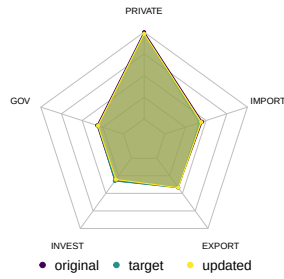


Figure 53: Italy rebase.

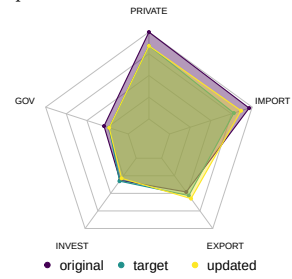


Figure 54: Jordan rebase.

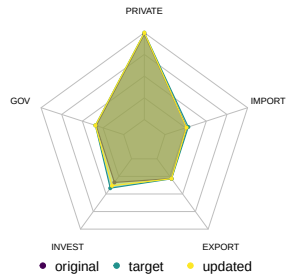


Figure 55: Japan rebase.

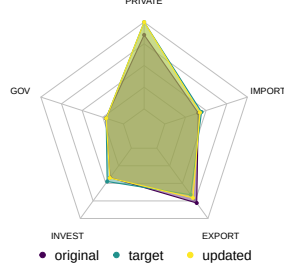


Figure 56: Kazakhstan rebase.

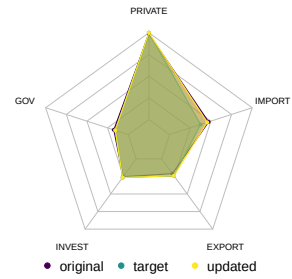


Figure 57: Kenya rebase.

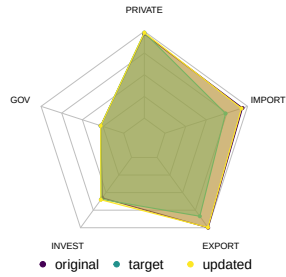


Figure 58: Korea rebase.

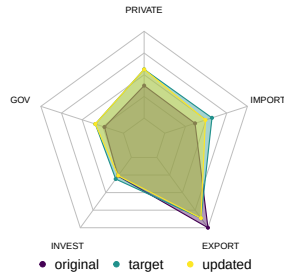


Figure 59: Kuwait rebase.

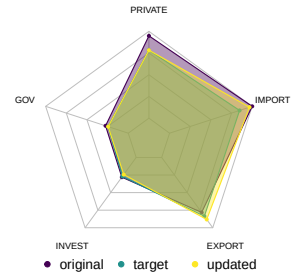


Figure 60: Lithuania rebase.

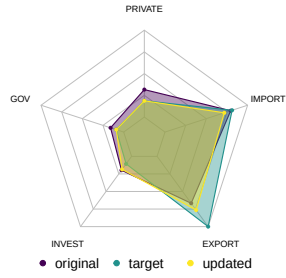


Figure 61: Luxembourg rebase.

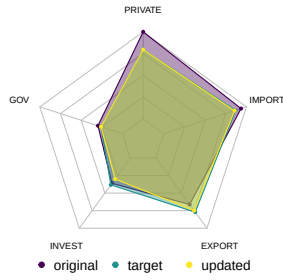


Figure 62: Latvia rebase.

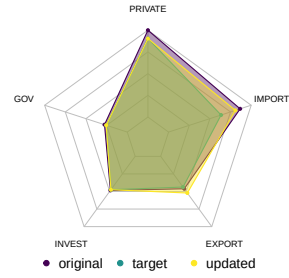


Figure 63: Rest of Western Africa rebase.

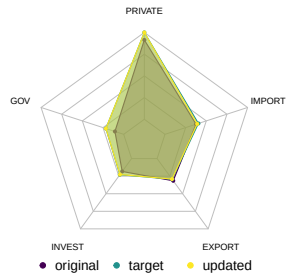


Figure 64: Madagascar rebase.

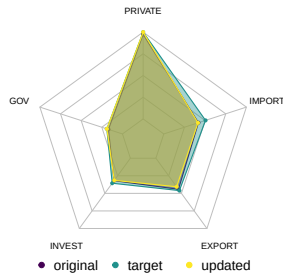


Figure 65: Mexico rebase.

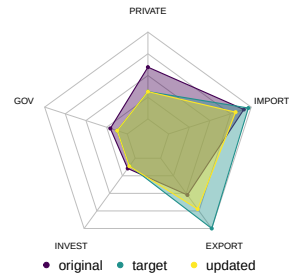


Figure 66: Malta rebase.

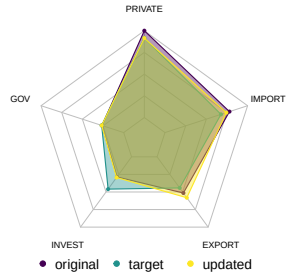


Figure 67: Mozambique rebase.

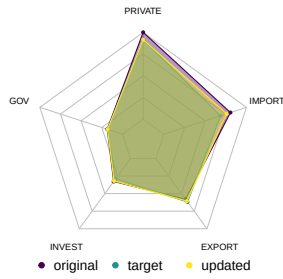


Figure 68: Mauritius rebase.

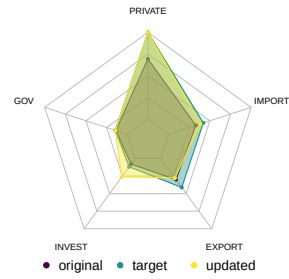


Figure 69: Malawi rebase.

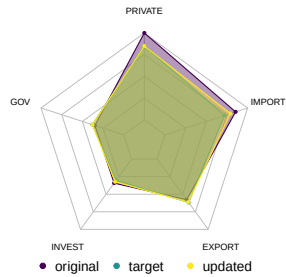


Figure 70: Namibia rebase.

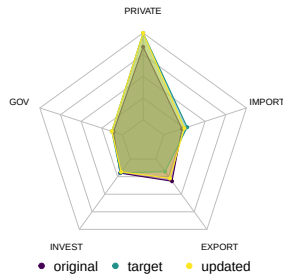


Figure 71: Nigeria rebase.

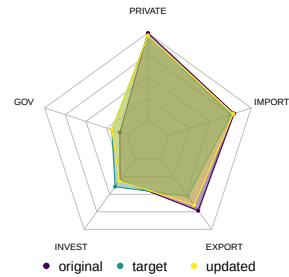


Figure 72: Nicaragua rebase.

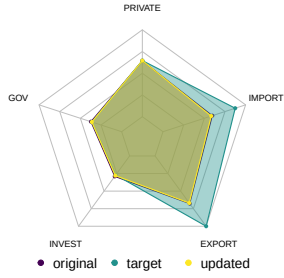


Figure 73: Netherlands rebase.

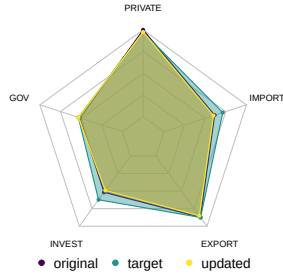


Figure 74: Rest of EFTA rebase.

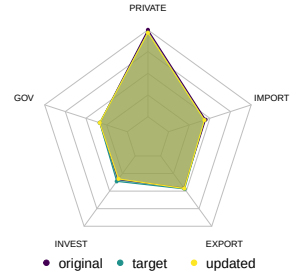


Figure 75: New Zealand rebase.

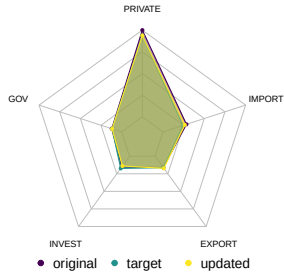


Figure 76: Pakistan rebase.

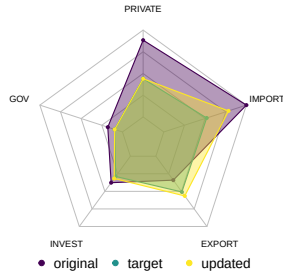


Figure 77: Panama rebase.

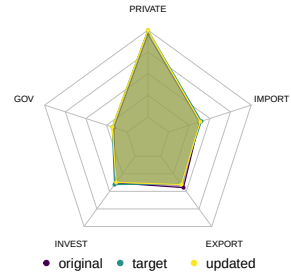


Figure 78: Peru rebase.

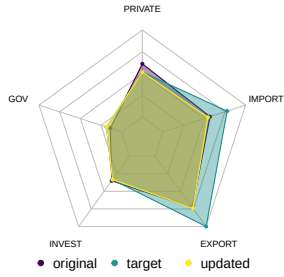


Figure 79: Petrol States rebase.

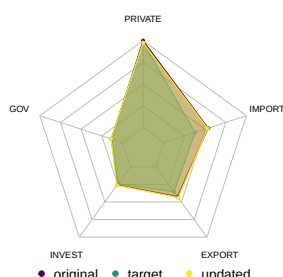


Figure 80: Philippines rebase.

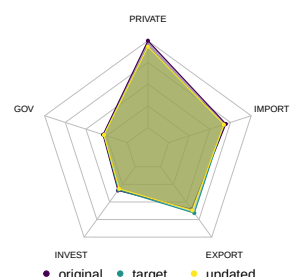


Figure 81: Poland rebase.

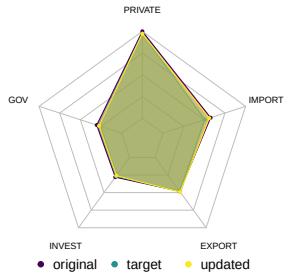


Figure 82: Portugal rebase.

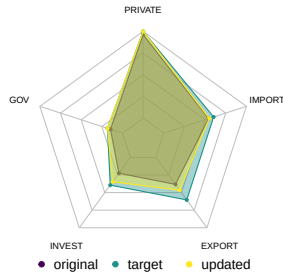


Figure 83: Paraguay rebase.

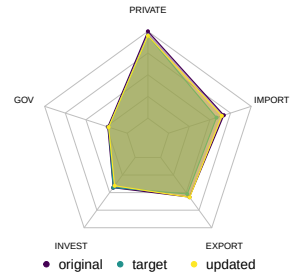


Figure 84: Romania rebase.

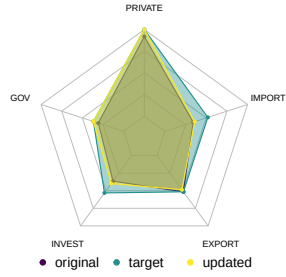


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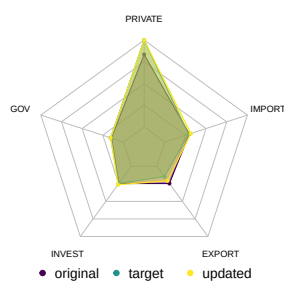


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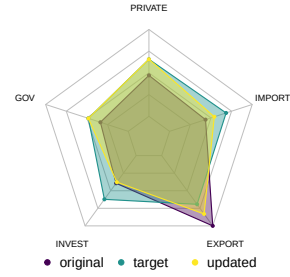


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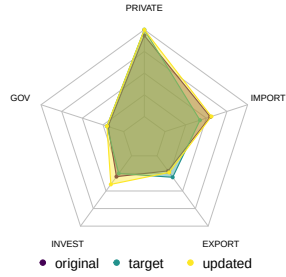


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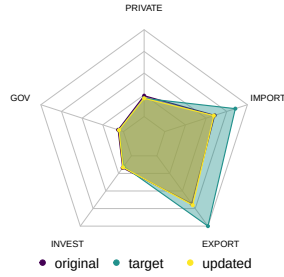


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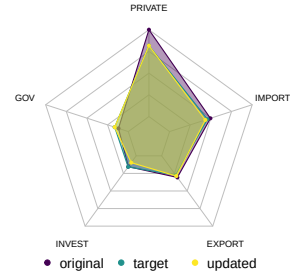


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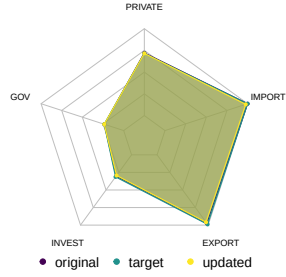


Figure 91: Slovakia rebase.

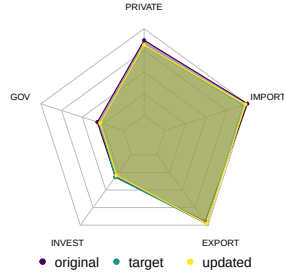


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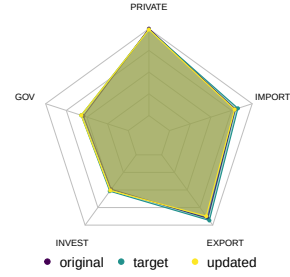


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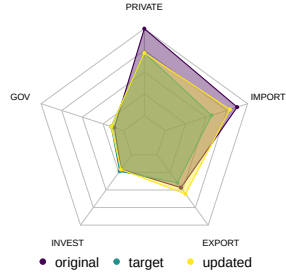


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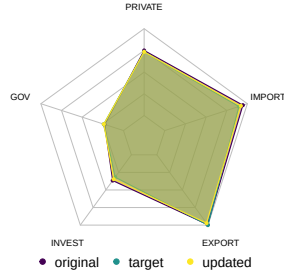


Figure 95: Thailand rebase.

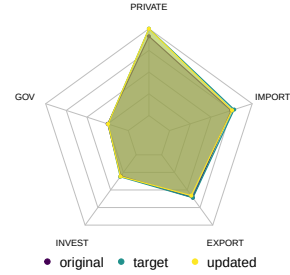


Figure 96: Tunisia rebase.

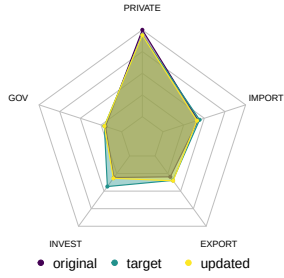


Figure 97: Turkey rebase.

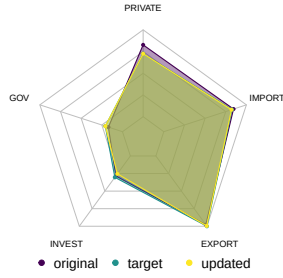


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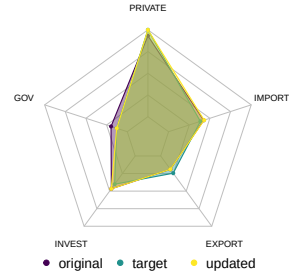


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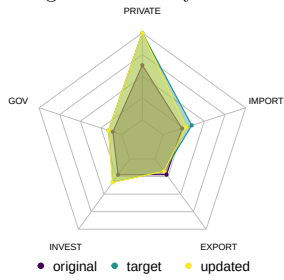


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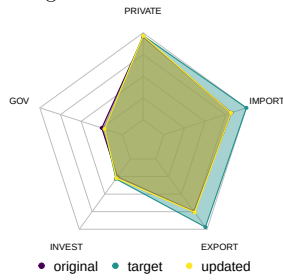


Figure 101: Ukraine rebase.

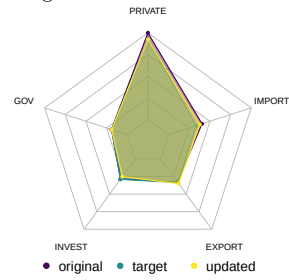


Figure 102: Uruguay rebase.

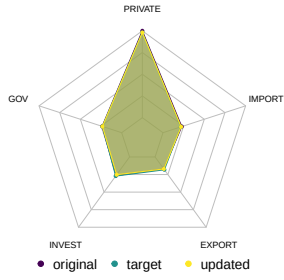


Figure 103: United States of America rebase.

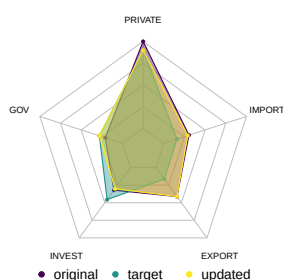


Figure 104: Venezuela rebase.

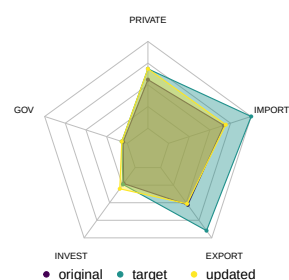


Figure 105: Viet Nam rebase.

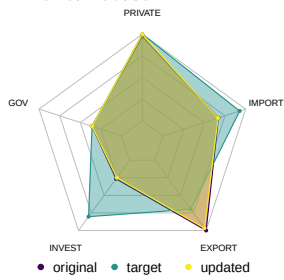


Figure 106: South Central Africa rebase.

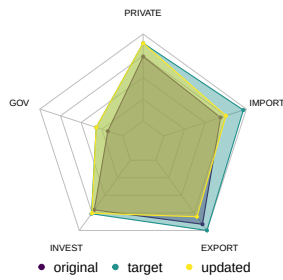


Figure 107: Central Africa rebase.

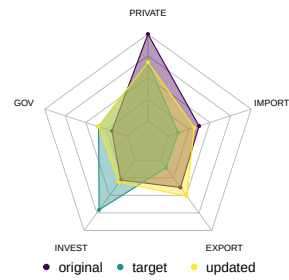


Figure 108: Rest of Eastern Africa rebase.

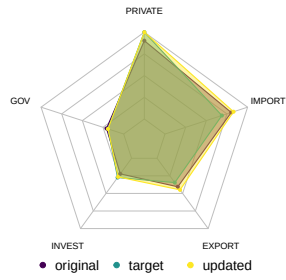


Figure 109: Rest of Eastern Europe rebase.

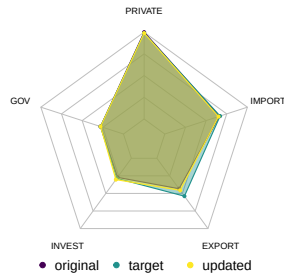


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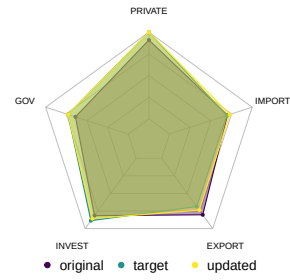


Figure 111: Rest of North Africa rebase.

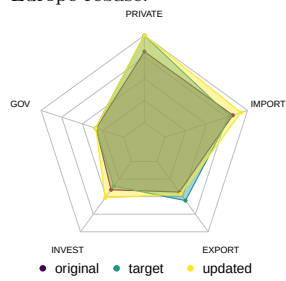


Figure 112: Rest of Oceania rebase.

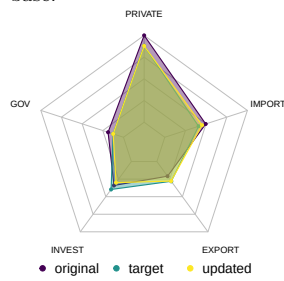


Figure 113: Rest of South Asia rebase.

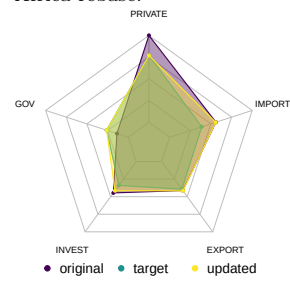


Figure 114: Rest of Southeast Asia rebase.

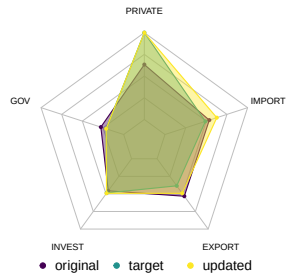


Figure 115: Rest of Central Asia rebase.

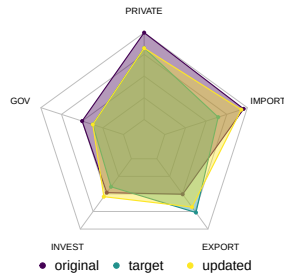


Figure 116: Rest of the World rebase.

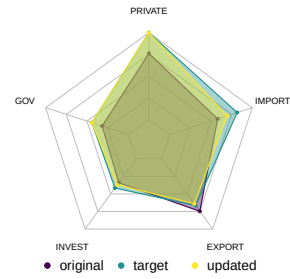


Figure 117: Rest of Western Asia rebase.

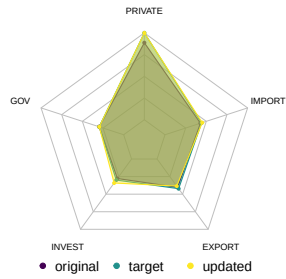


Figure 118: South Africa+ rebase.

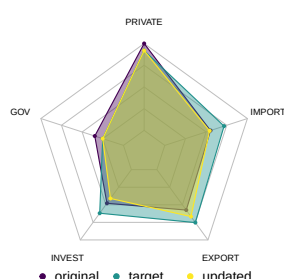


Figure 119: Zambia rebase.

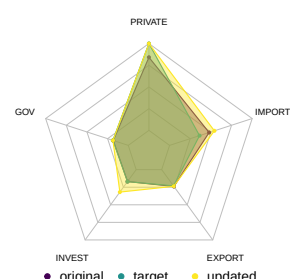


Figure 120: Zimbabwe rebase.

6.4. Land supply sensitivity analysis: all regions

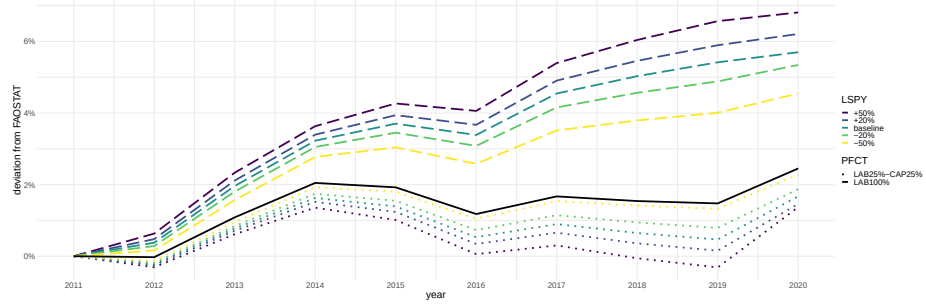


Figure 121: Albania: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

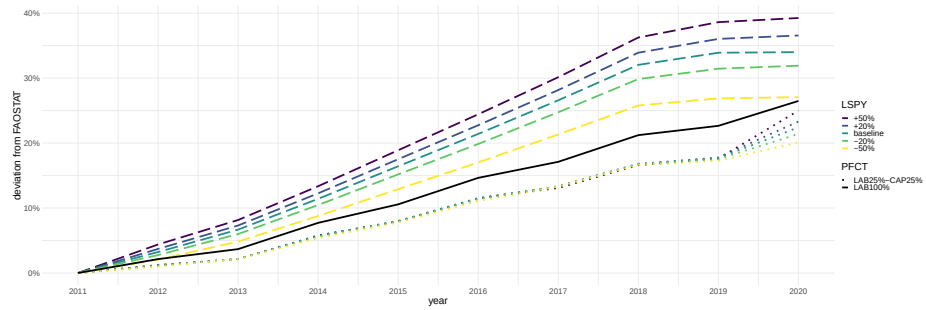


Figure 122: Argentina: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

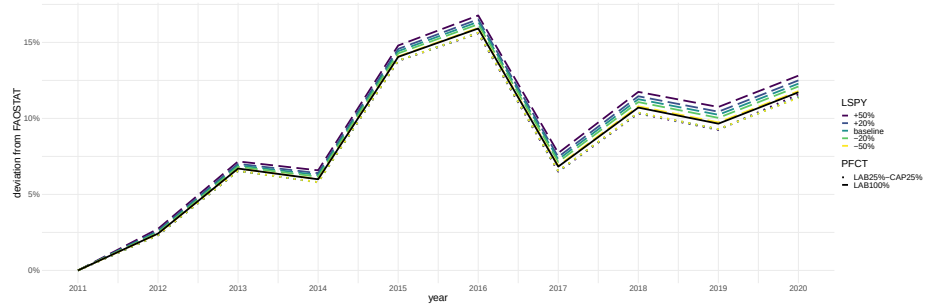


Figure 123: Australia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

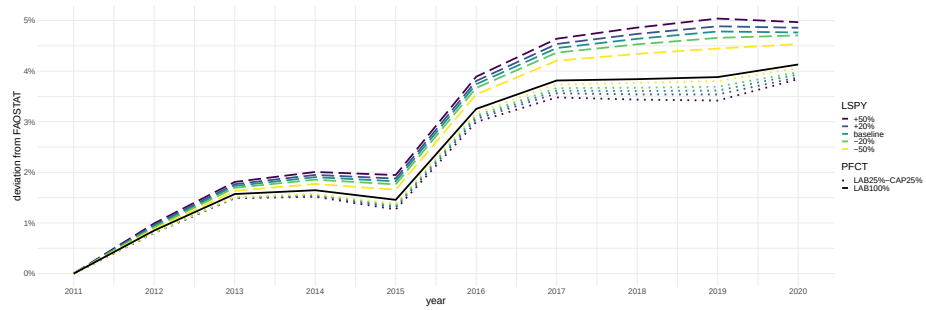


Figure 124: Austria: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.



Figure 125: Belgium: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

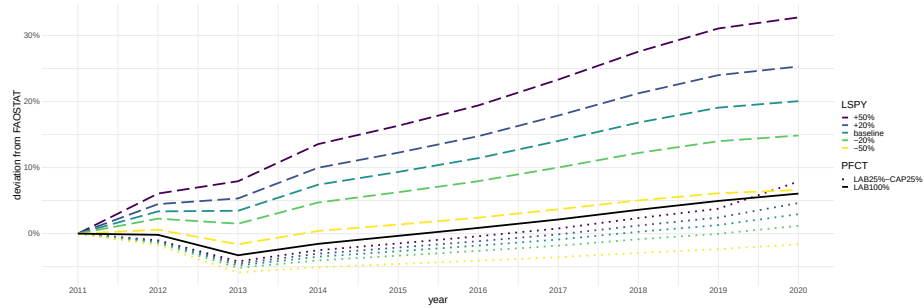


Figure 126: Benin: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

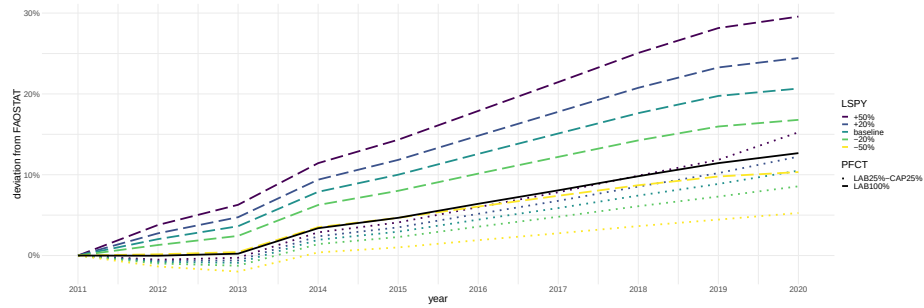


Figure 127: Burkina Faso: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

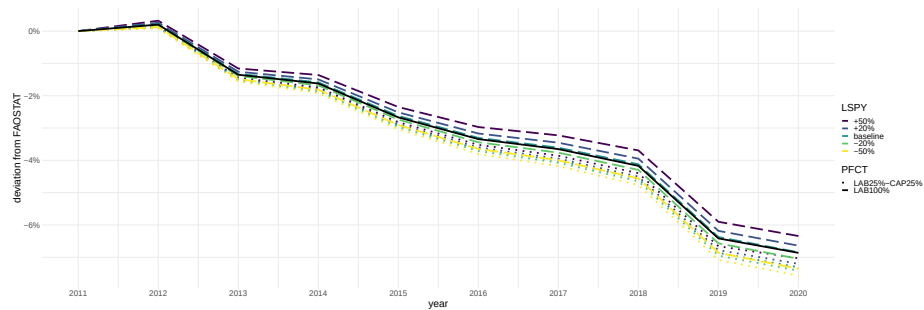


Figure 128: Bangladesh: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

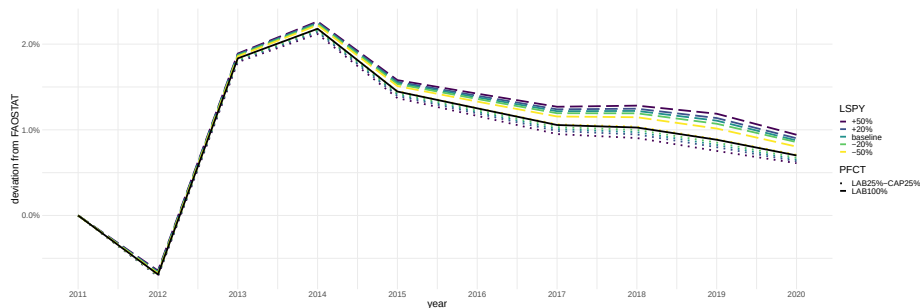


Figure 129: Bulgaria: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

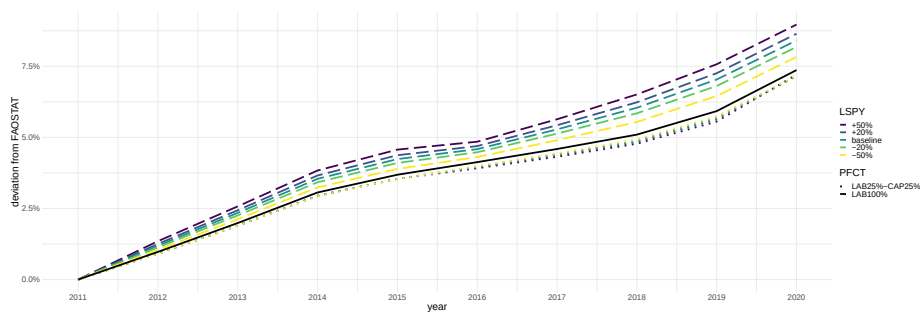


Figure 130: Belarus: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

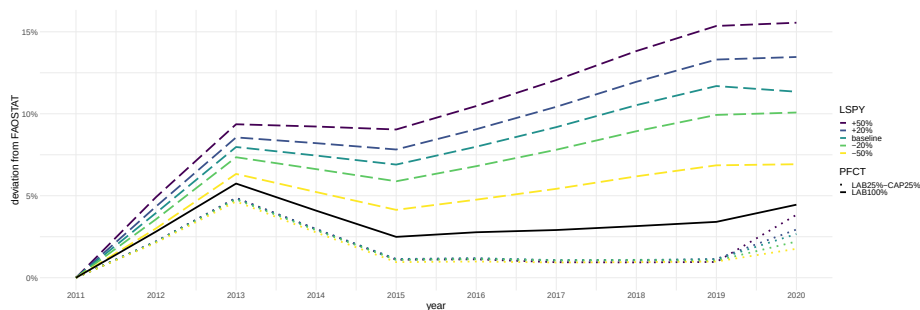


Figure 131: Rest of Central America: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

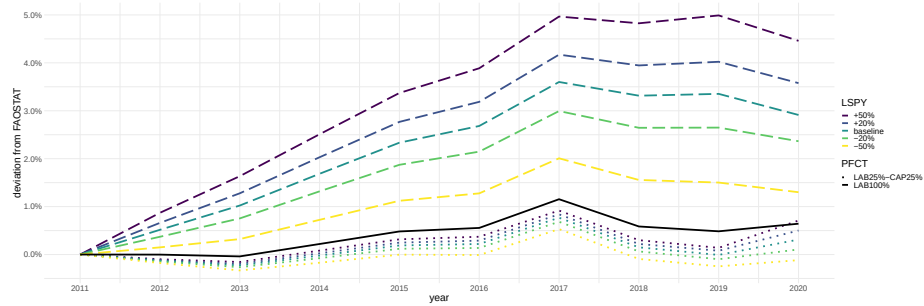


Figure 132: Bolivia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

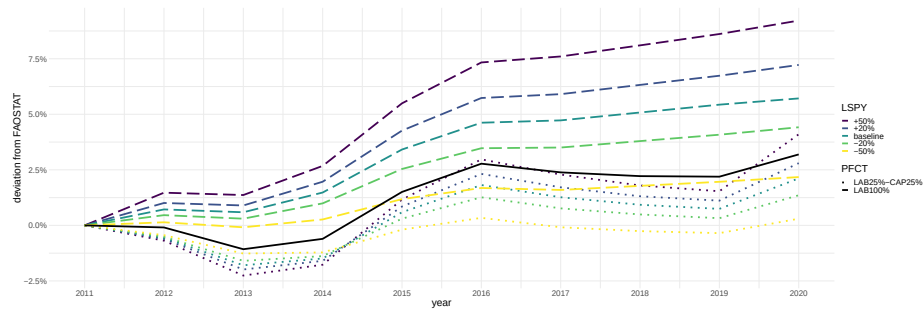


Figure 133: Brazil: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

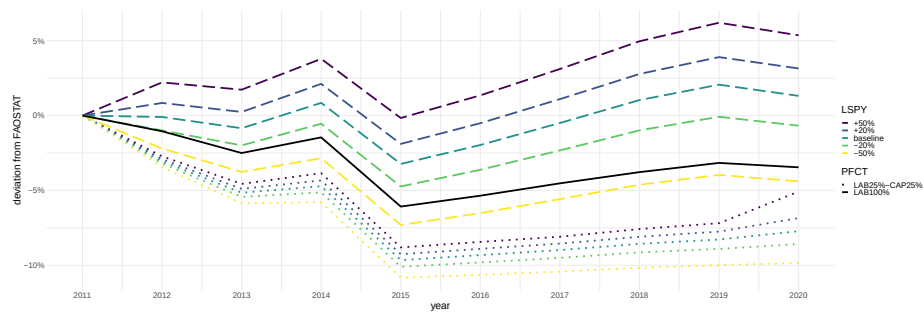


Figure 134: Malaysia+: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

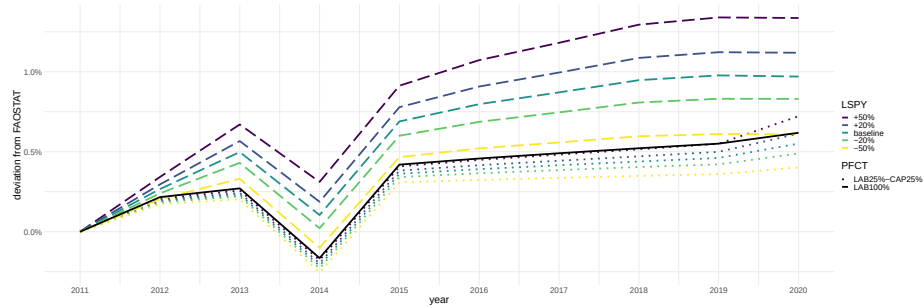


Figure 135: Botswana: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

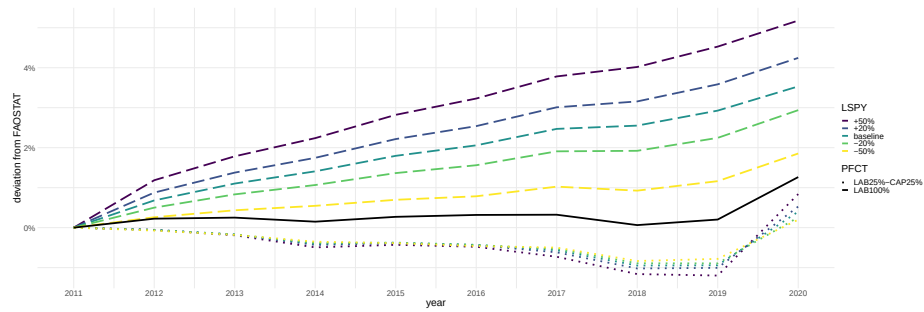


Figure 136: Canada: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

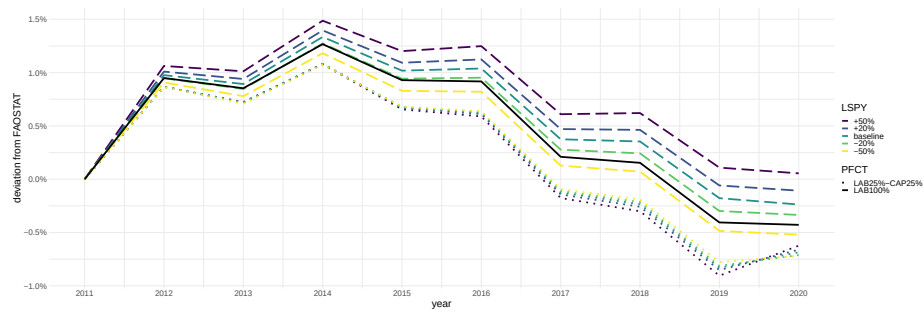


Figure 137: Caribbean: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

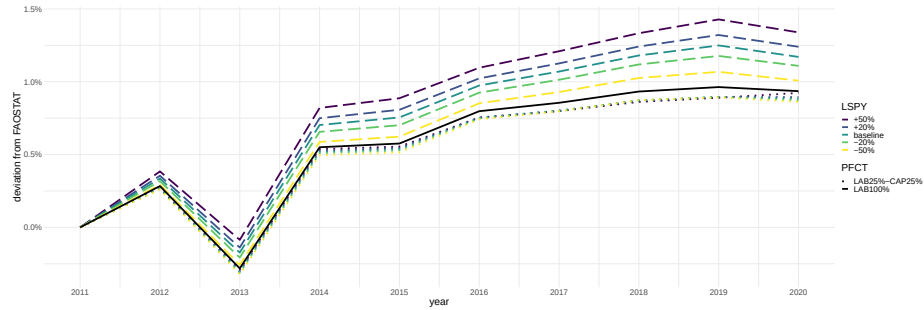


Figure 138: The Caucasus: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

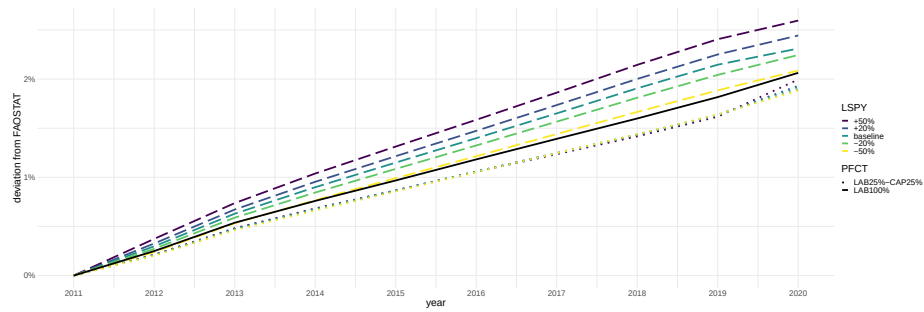


Figure 139: Switzerland: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

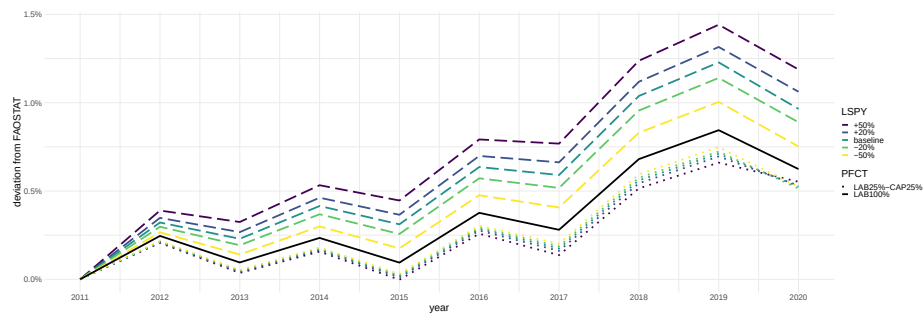


Figure 140: Chile: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

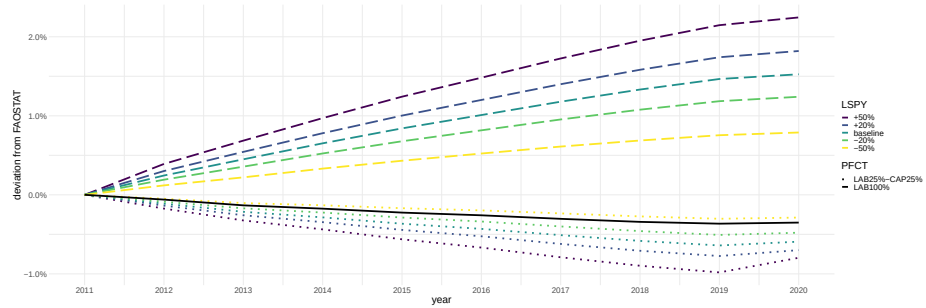


Figure 141: China: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

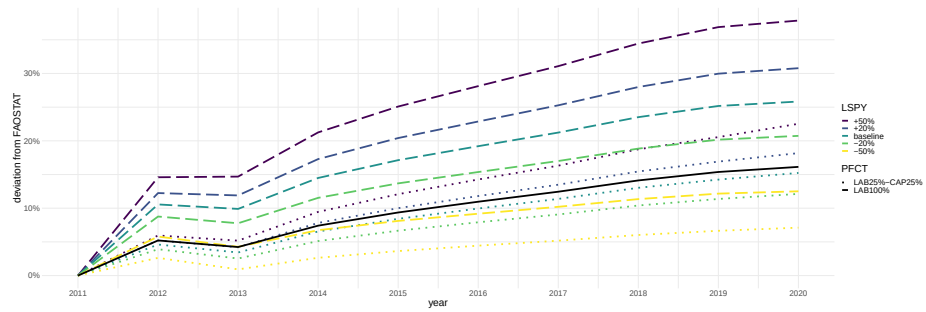


Figure 142: Cote d'Ivoire: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

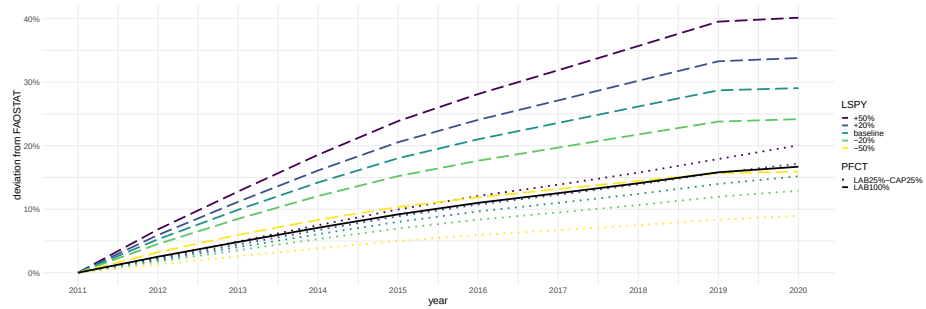


Figure 143: Cameroon: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

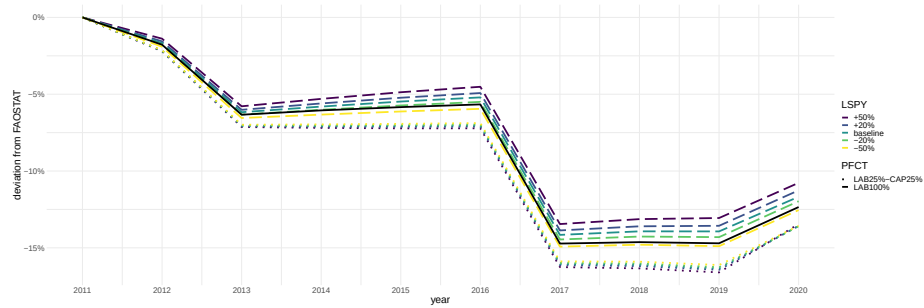


Figure 144: Colombia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

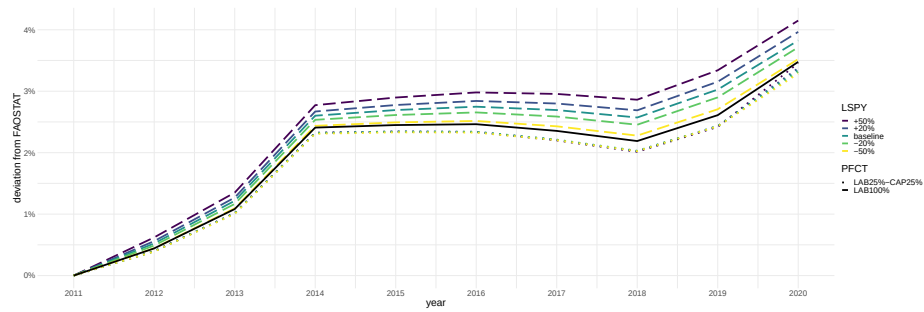


Figure 145: Costa Rica: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

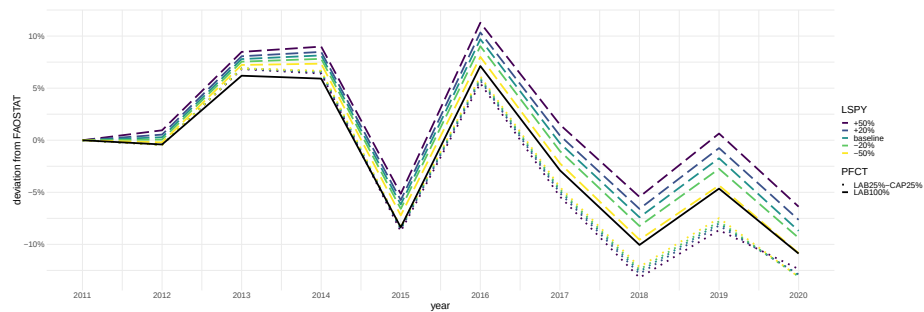


Figure 146: Cyprus: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

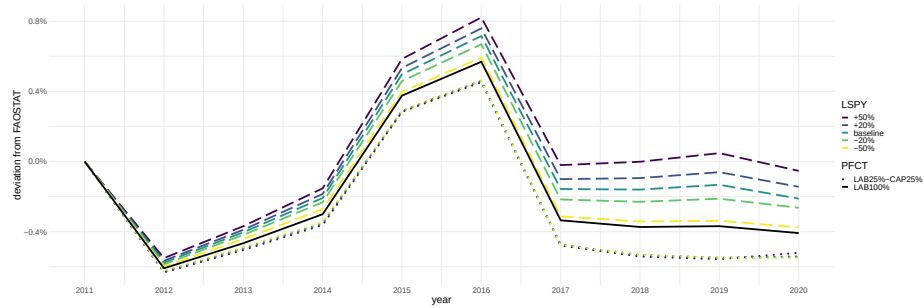


Figure 147: Czech Republic: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

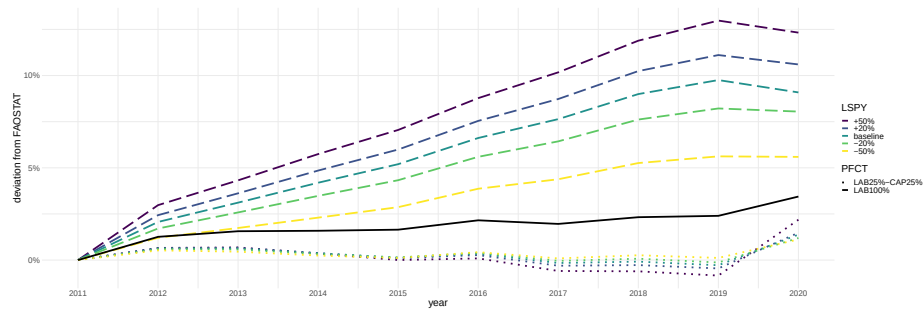


Figure 148: Germany: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

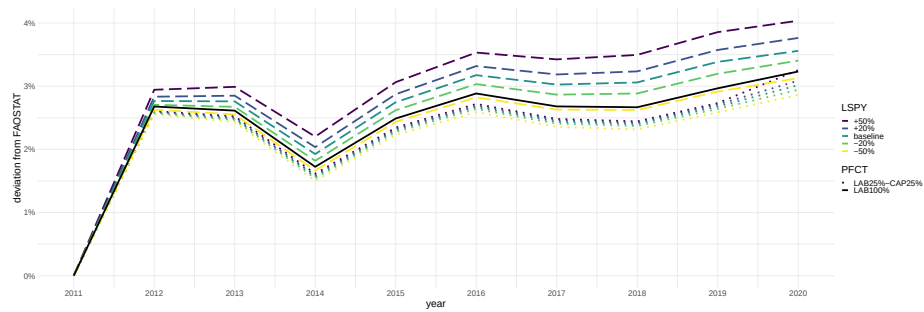


Figure 149: Denmark: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

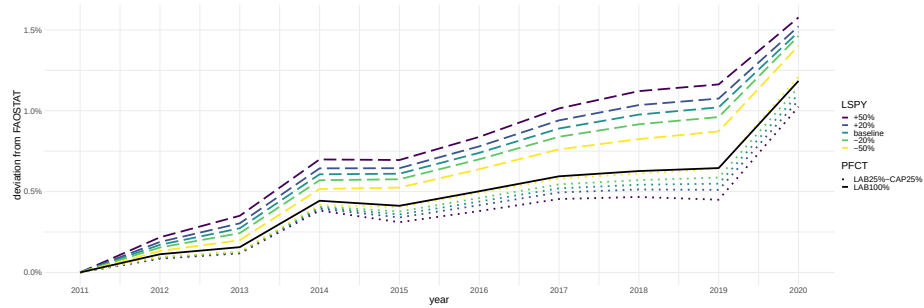


Figure 150: Rest of East Asia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

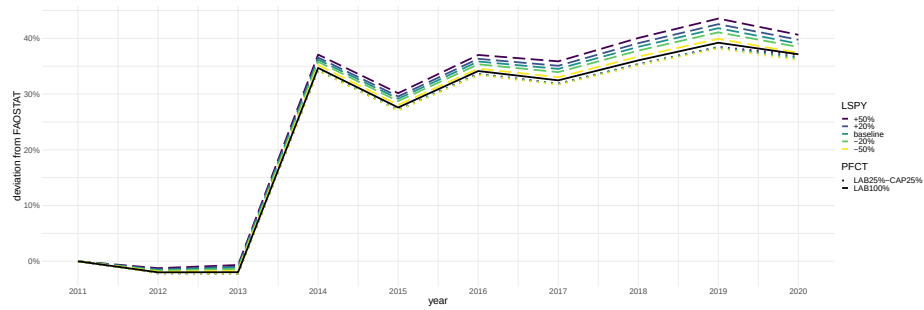


Figure 151: Ecuador: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

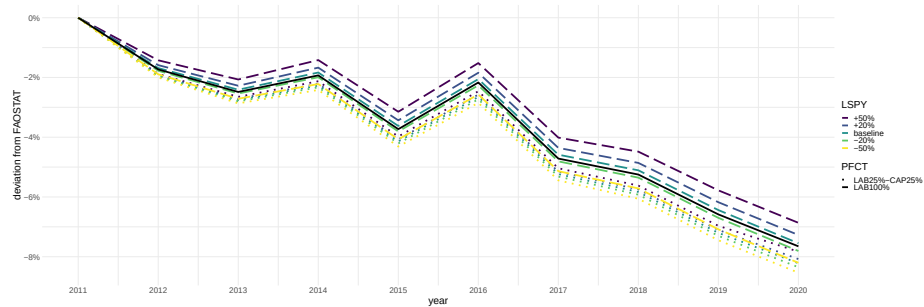


Figure 152: Egypt: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

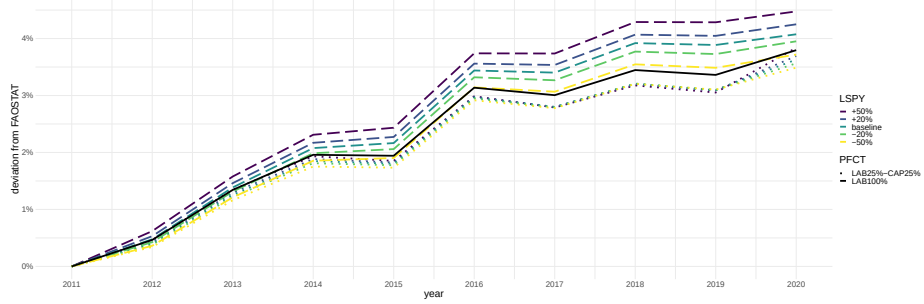


Figure 153: Spain: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

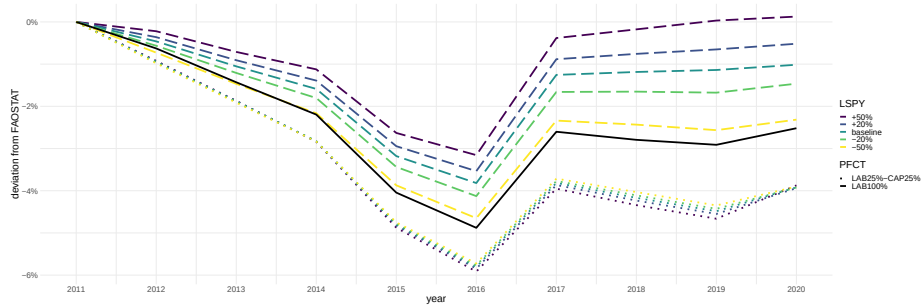


Figure 154: Estonia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

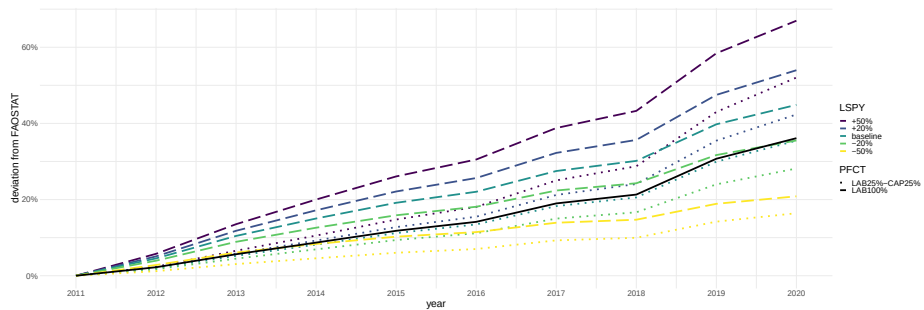


Figure 155: Ethiopia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

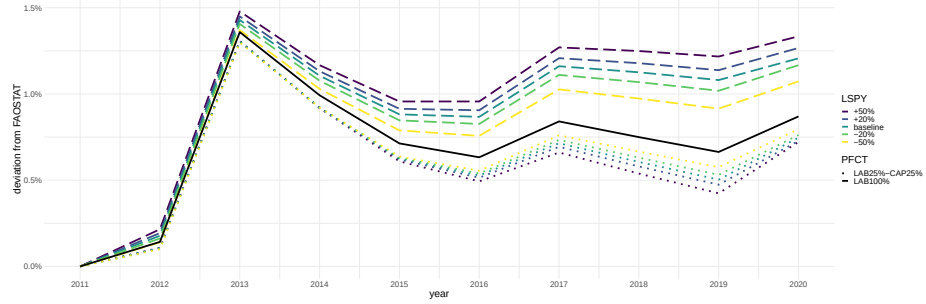


Figure 156: Finland: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

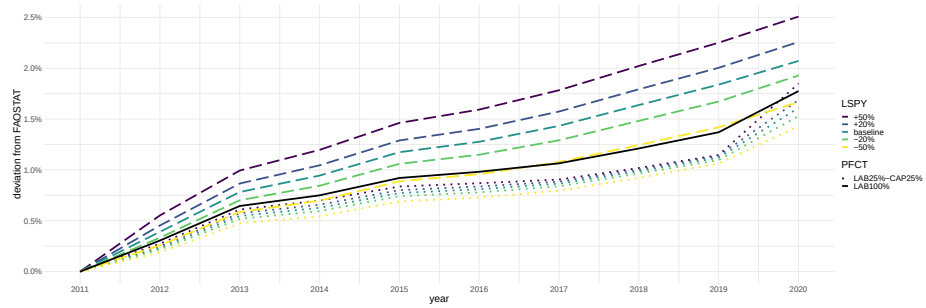


Figure 157: France: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

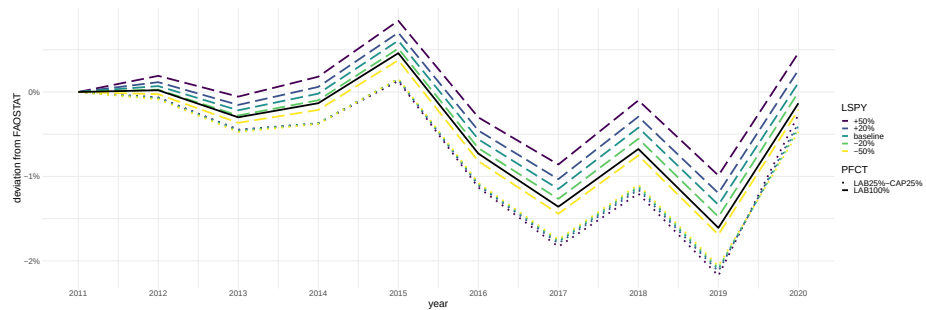


Figure 158: United Kingdom: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

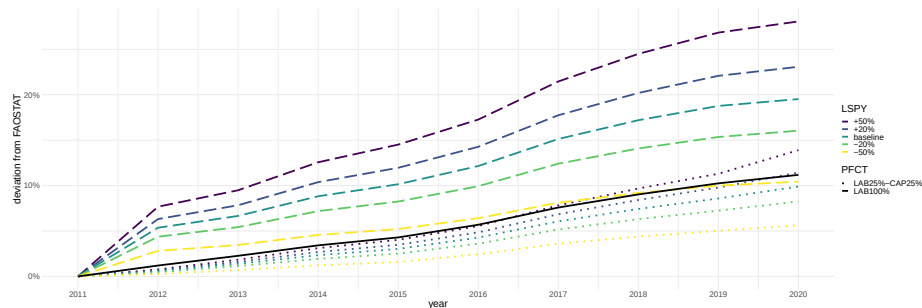


Figure 159: Ghana: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

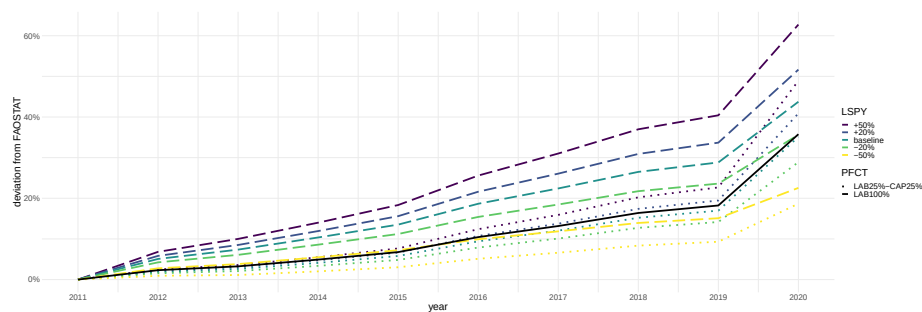


Figure 160: Guinea: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

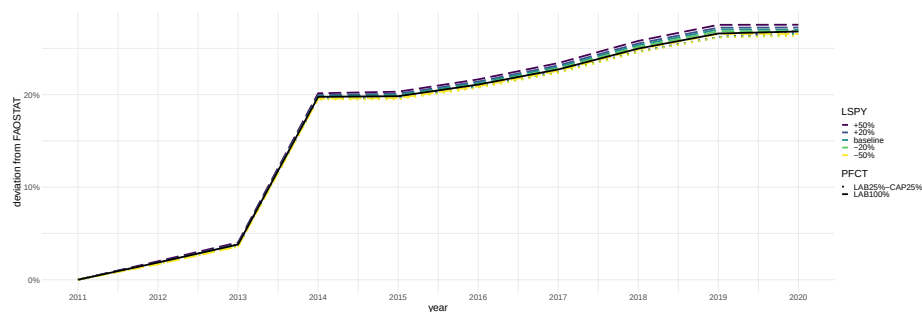


Figure 161: Greece: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

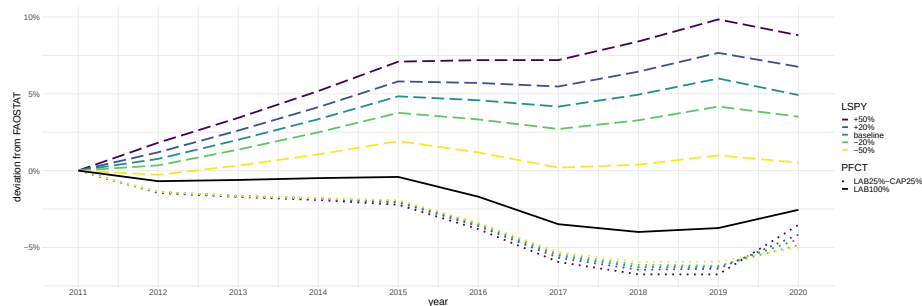


Figure 162: Honduras: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

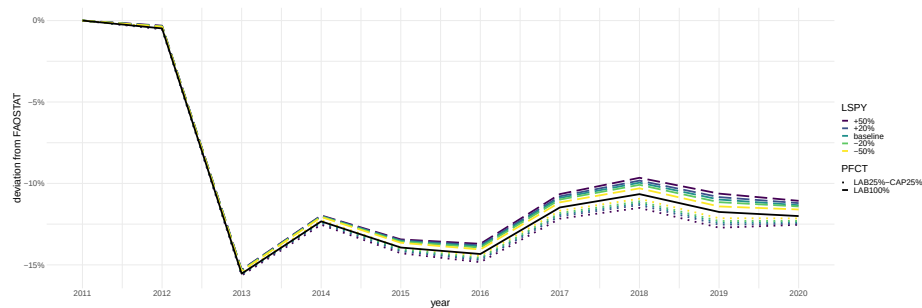


Figure 163: Croatia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

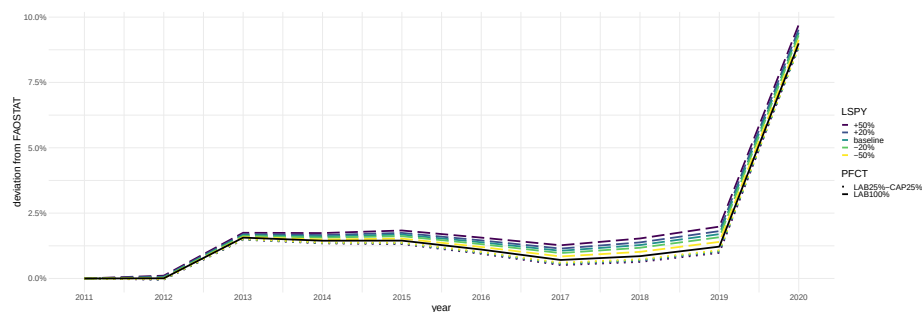


Figure 164: Hungary: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

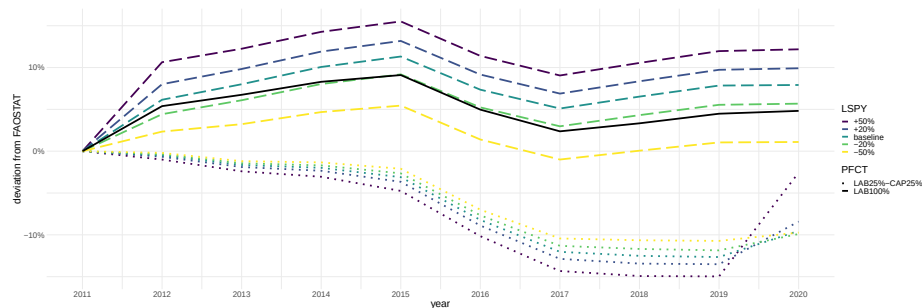


Figure 165: Indonesia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

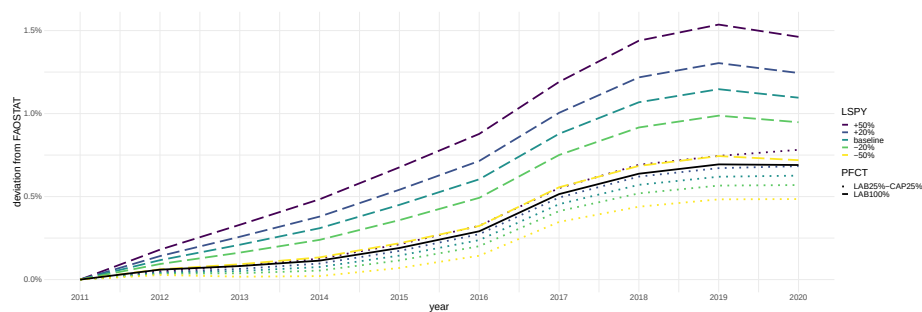


Figure 166: India: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

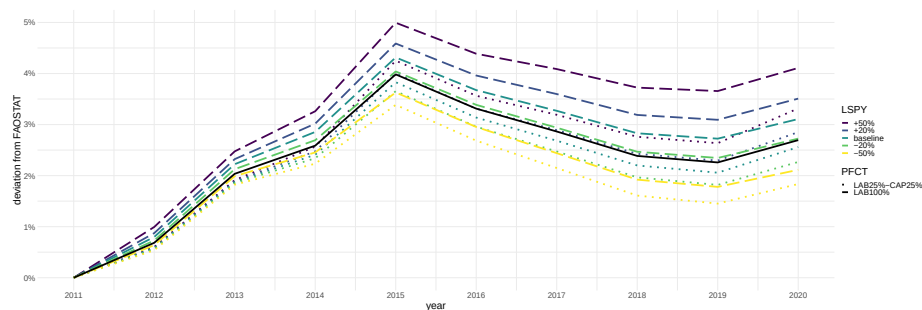


Figure 167: Ireland: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

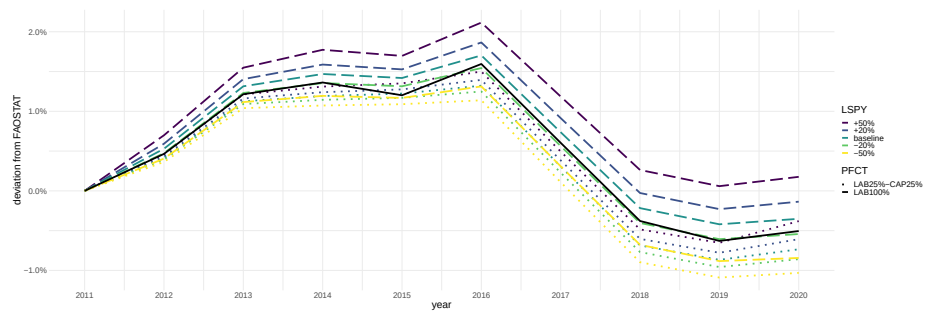


Figure 168: Iran Islamic Republic of: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

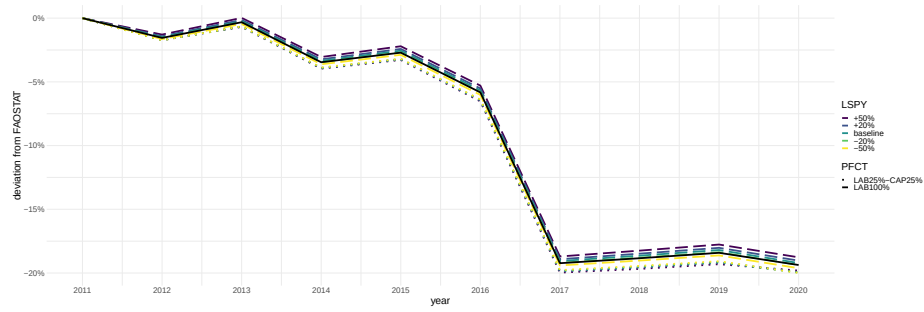


Figure 169: Israel: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

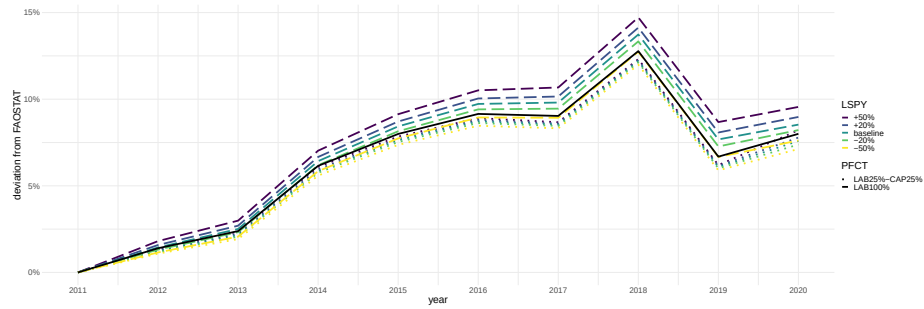


Figure 170: Italy: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

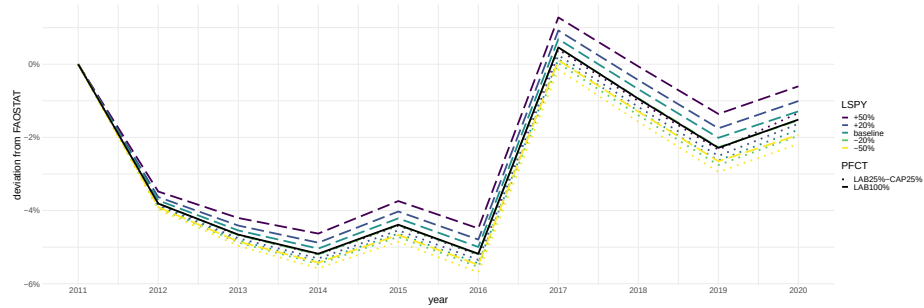


Figure 171: Jordan: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

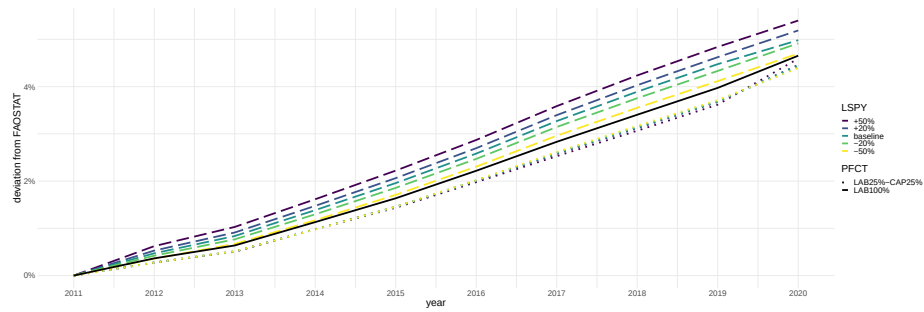


Figure 172: Japan: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

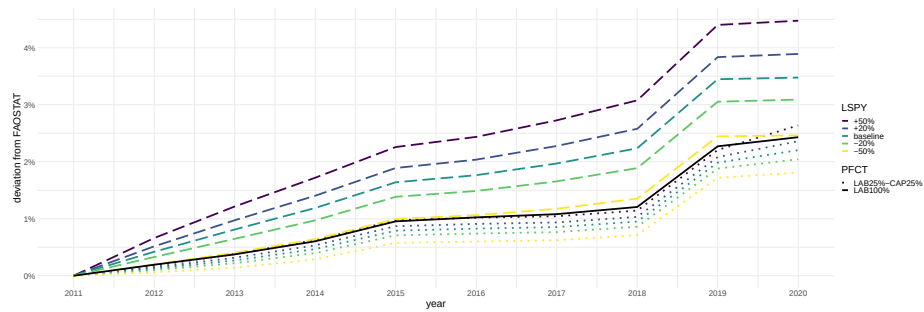


Figure 173: Kazakhstan: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

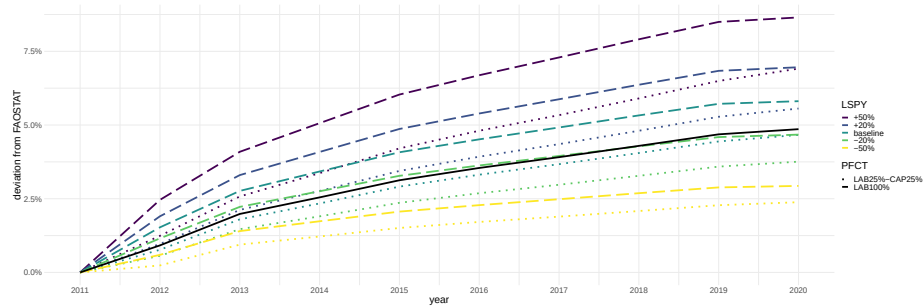


Figure 174: Kenya: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

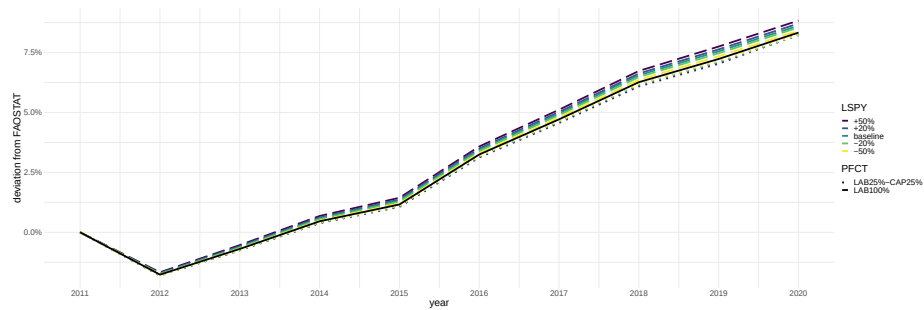


Figure 175: Korea: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

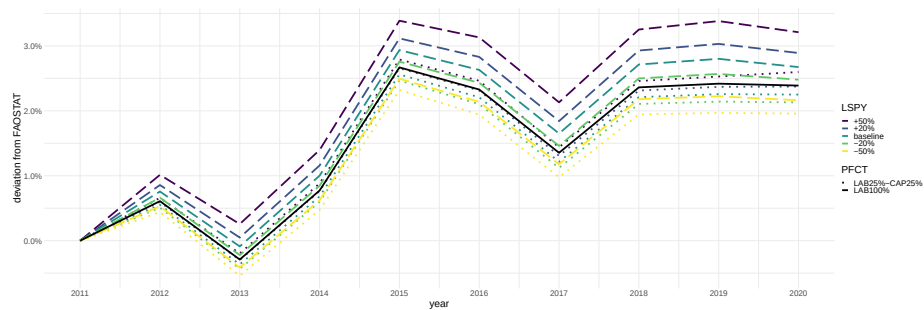


Figure 176: Kuwait: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

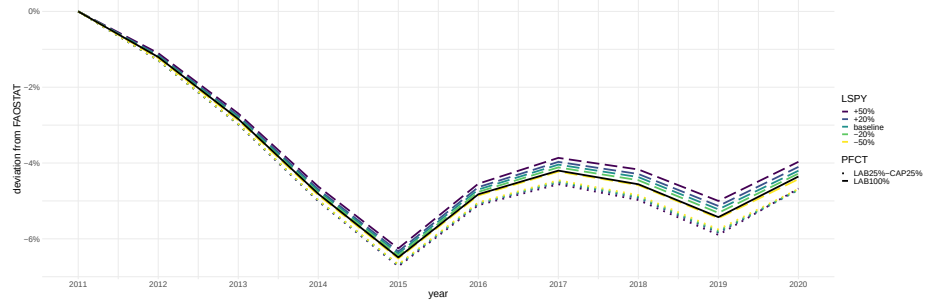


Figure 177: Lithuania: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

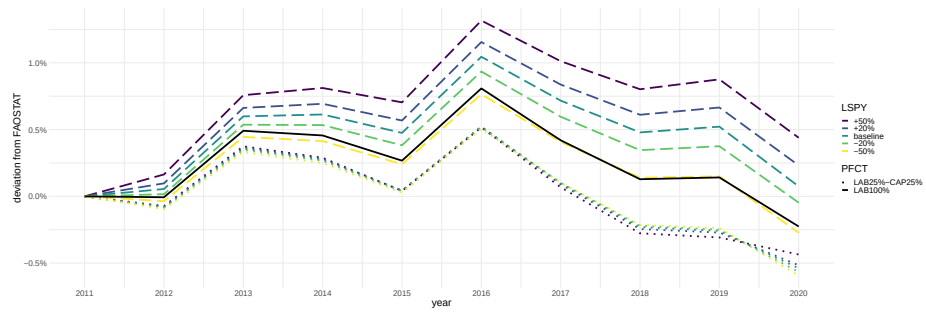


Figure 178: Luxembourg: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

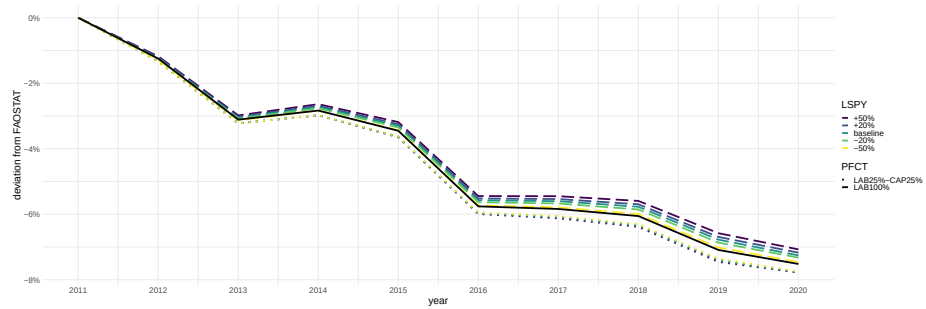


Figure 179: Latvia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

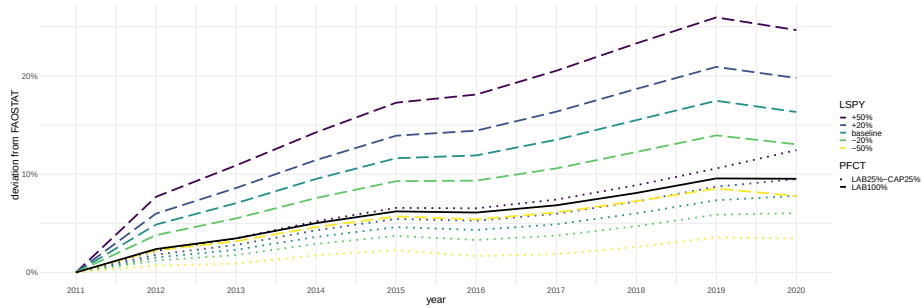


Figure 180: Rest of Western Africa: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

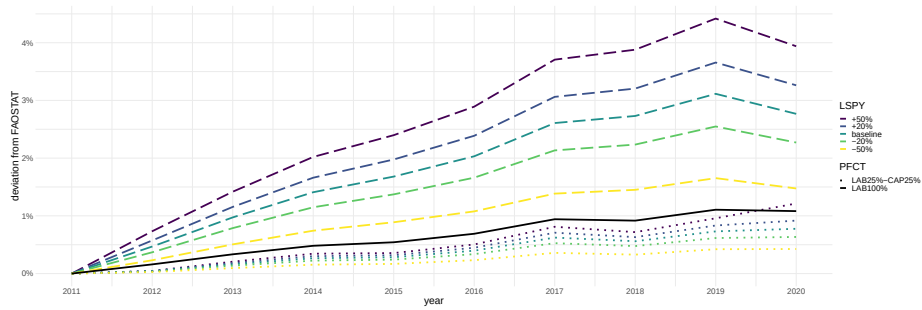


Figure 181: Madagascar: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

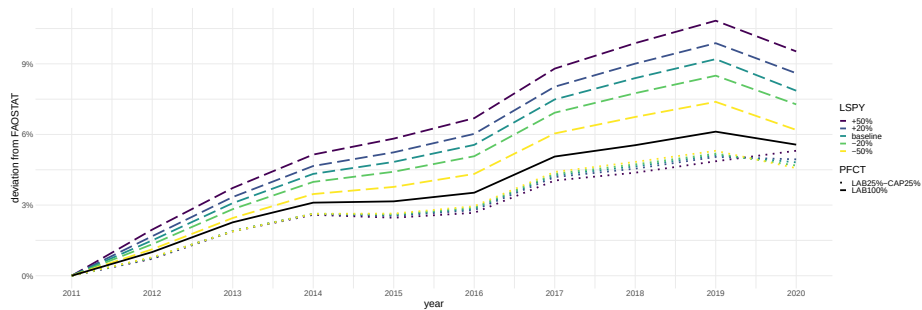


Figure 182: Mexico: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

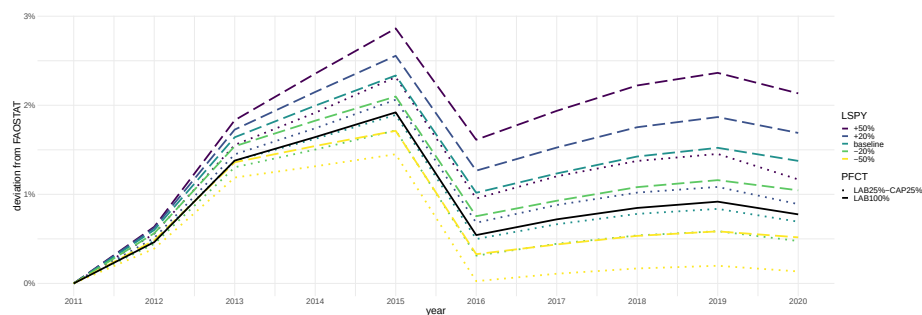


Figure 183: Malta: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

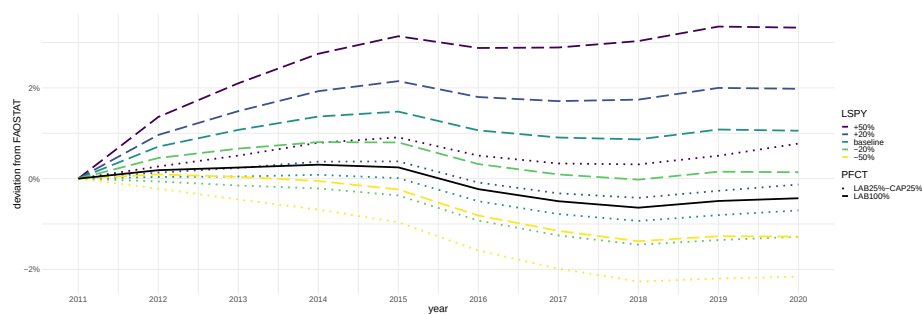


Figure 184: Mozambique: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.



Figure 185: Mauritius: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

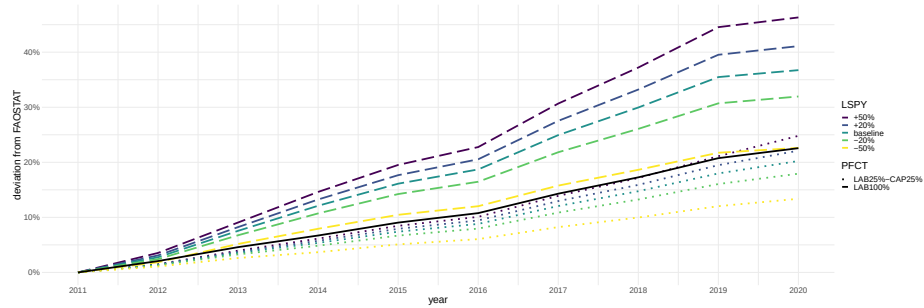


Figure 186: Malawi: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

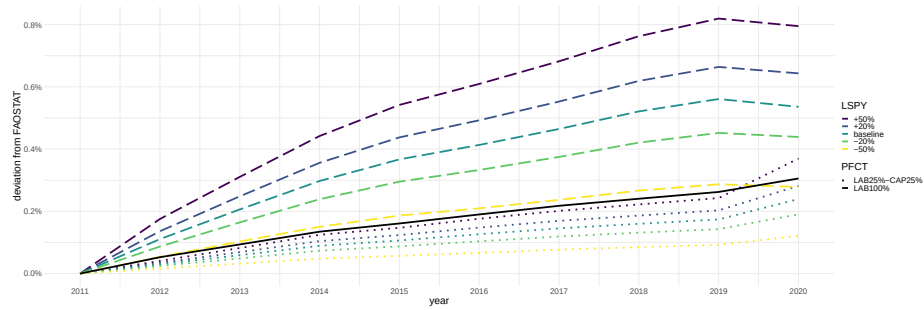


Figure 187: Namibia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

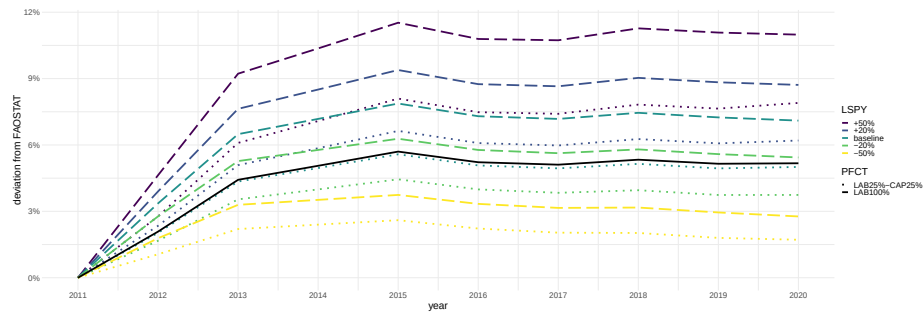


Figure 188: Nigeria: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

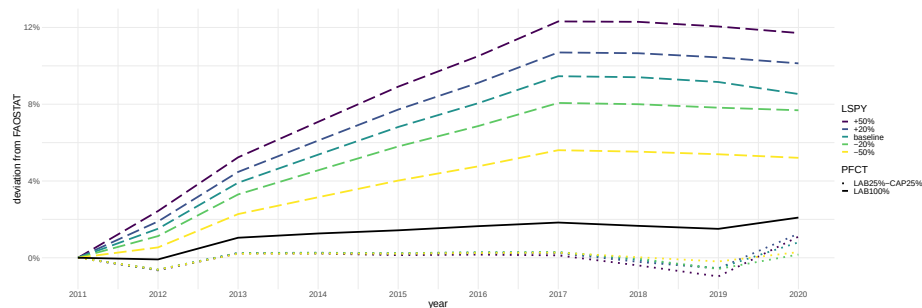


Figure 189: Nicaragua: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.



Figure 190: Netherlands: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

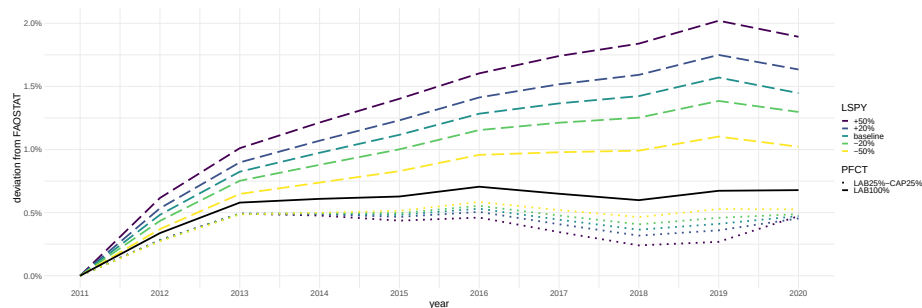


Figure 191: Rest of EFTA: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

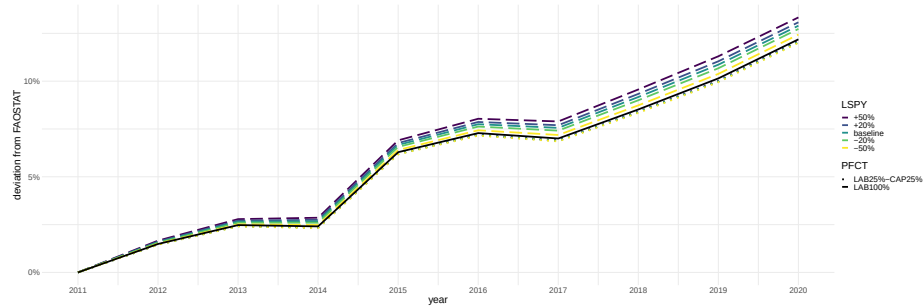


Figure 192: New Zealand: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

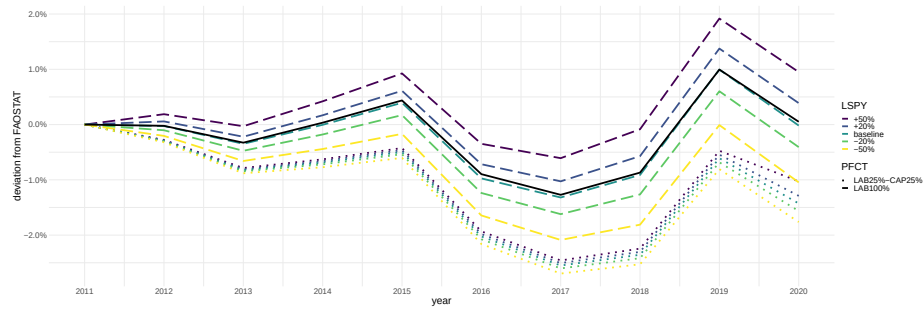


Figure 193: Pakistan: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

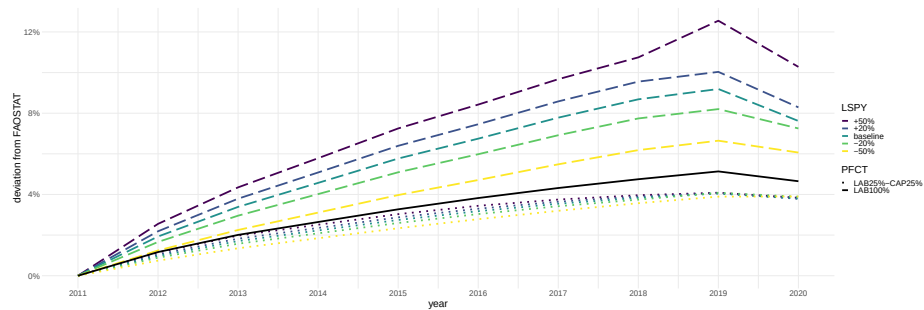


Figure 194: Panama: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

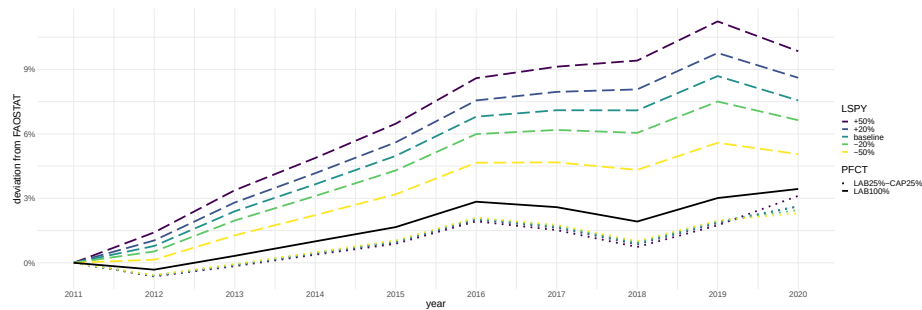


Figure 195: Peru: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

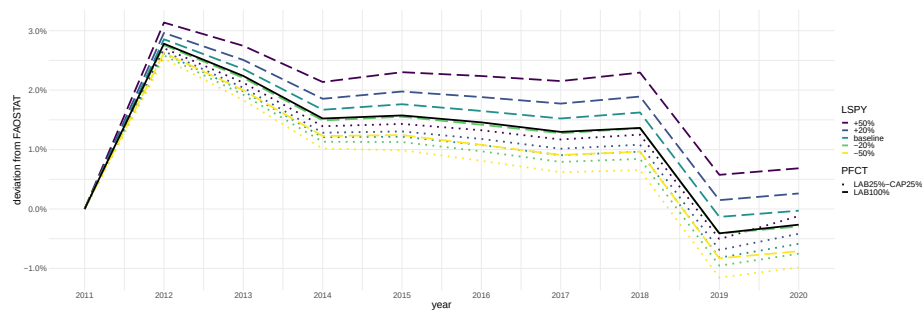


Figure 196: Petrol States: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

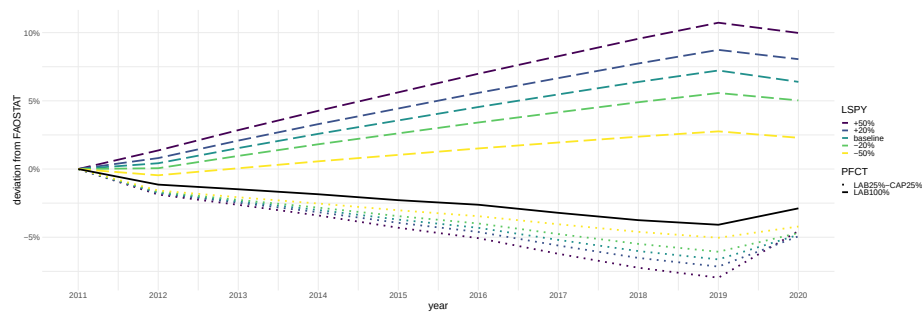


Figure 197: Philippines: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

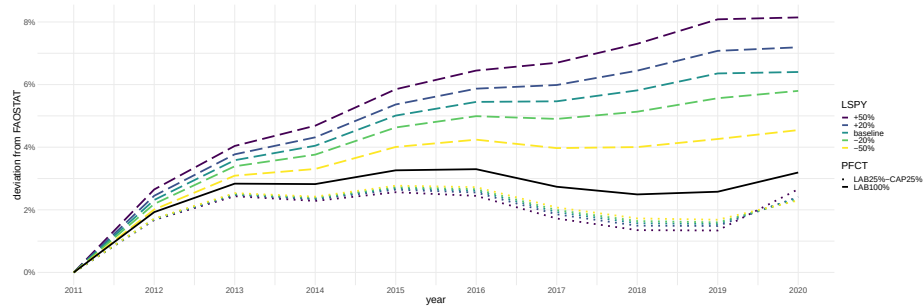


Figure 198: Poland: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

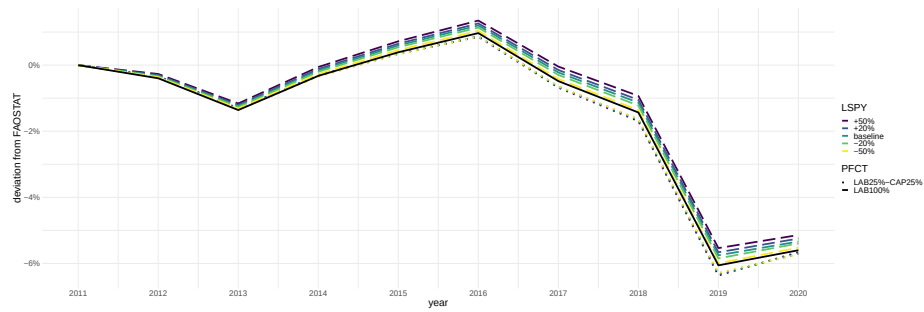


Figure 199: Portugal: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

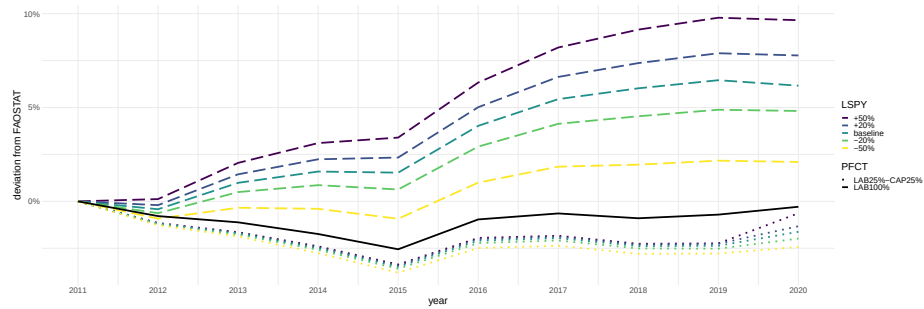


Figure 200: Paraguay: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

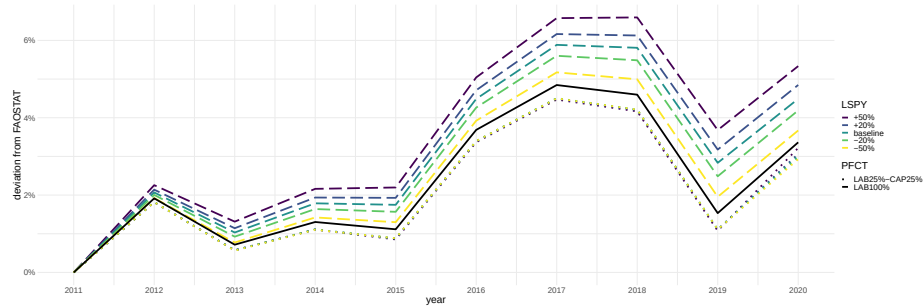


Figure 201: Romania: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

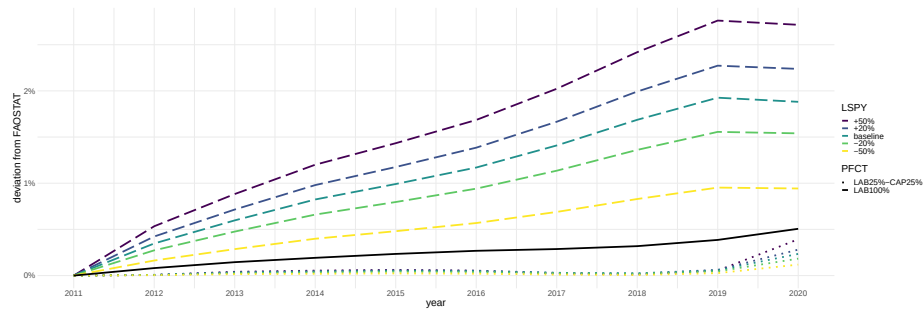


Figure 202: Russian Federation: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

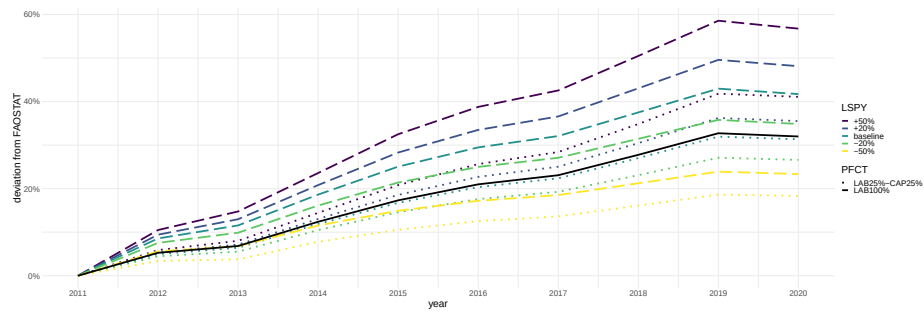


Figure 203: Rwanda: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

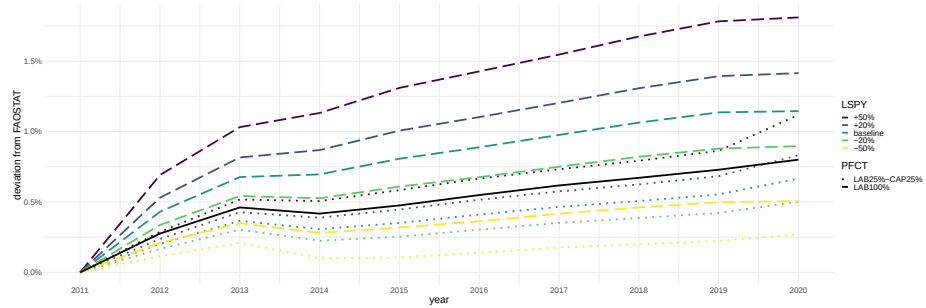


Figure 204: Saudi Arabia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

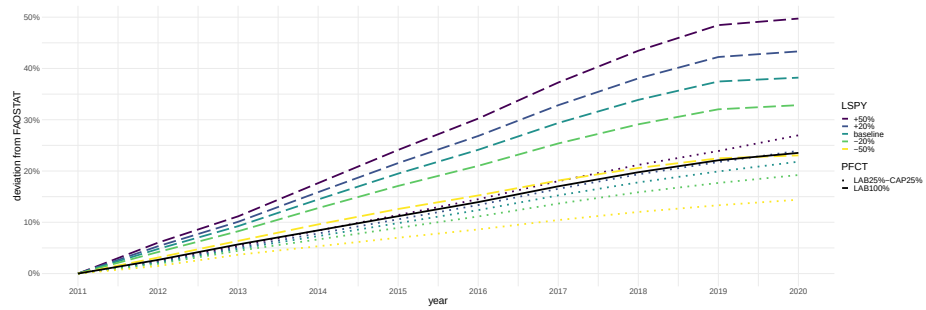


Figure 205: Senegal: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

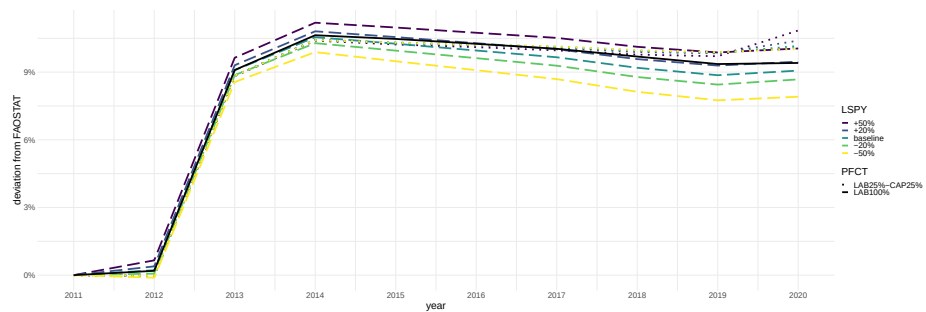


Figure 206: Singapore: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

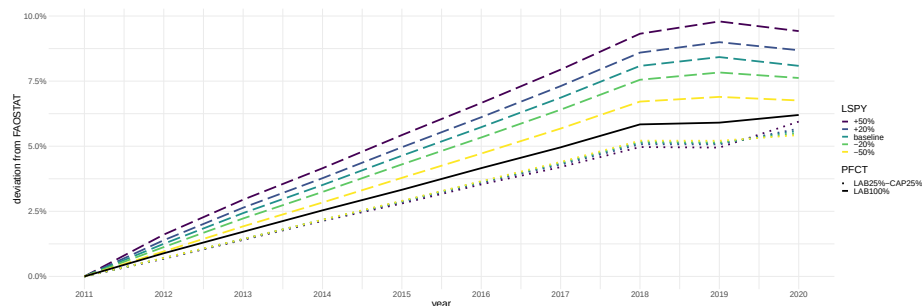


Figure 207: El Salvador: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

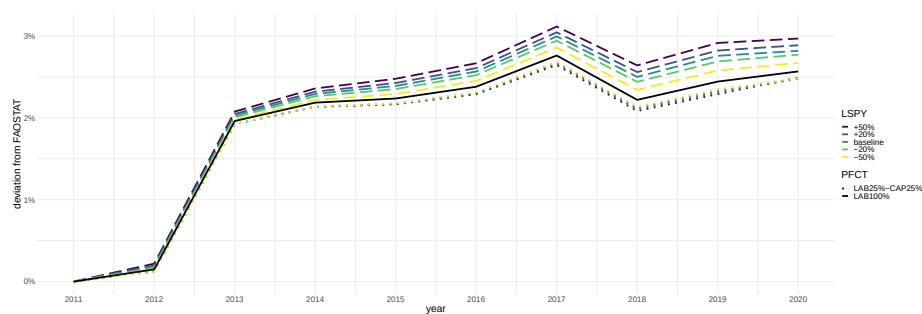


Figure 208: Slovakia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

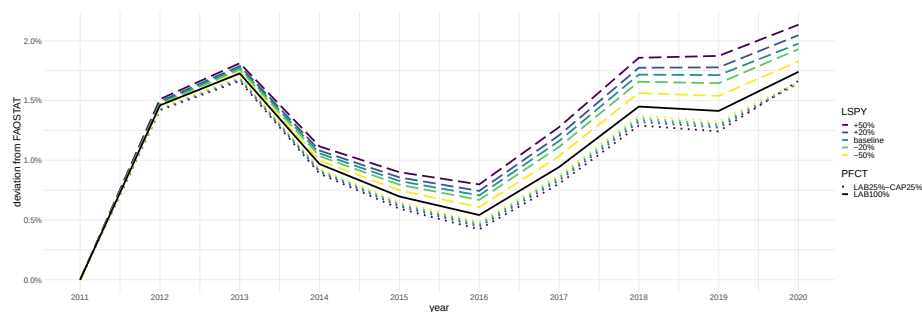


Figure 209: Slovenia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

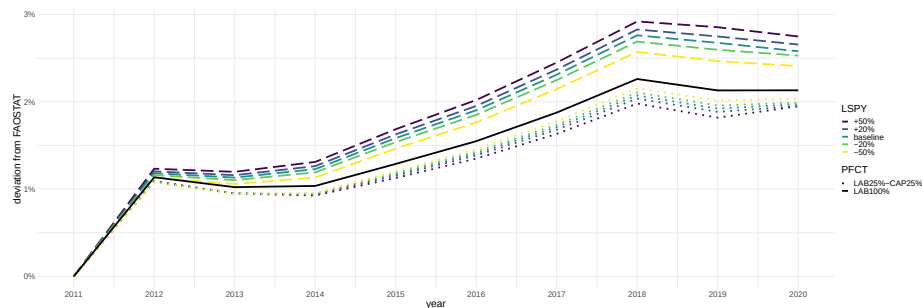


Figure 210: Sweden: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

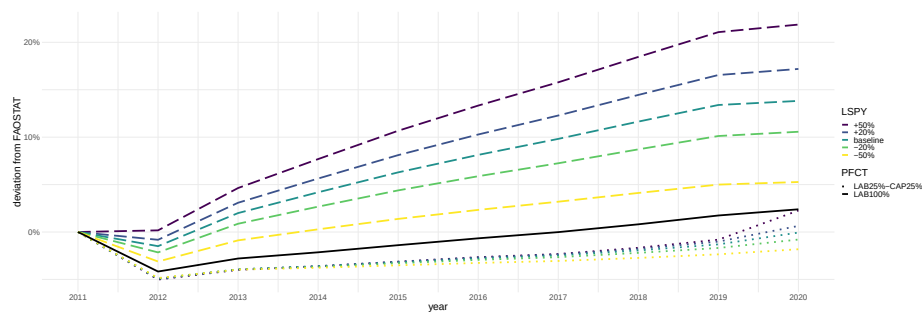


Figure 211: Togo: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

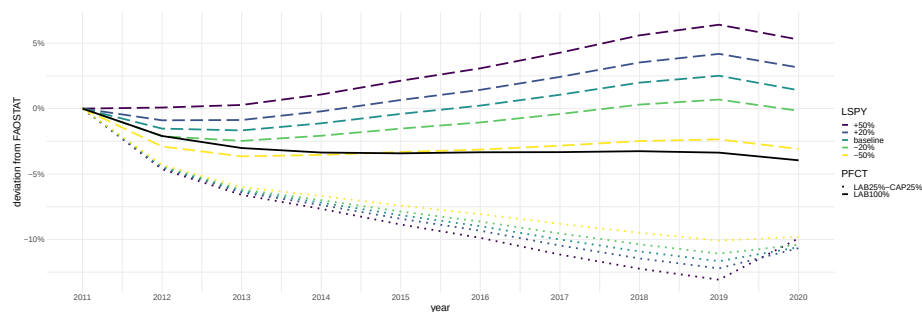


Figure 212: Thailand: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

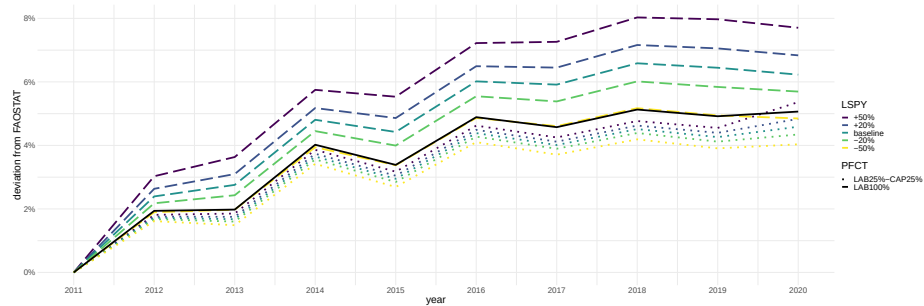


Figure 213: Tunisia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

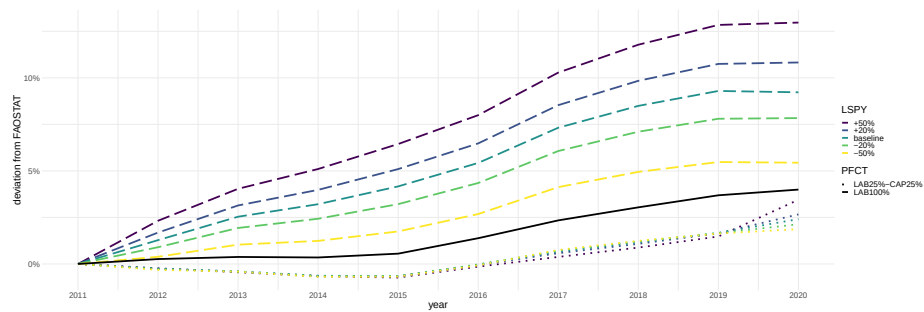


Figure 214: Turkey: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.



Figure 215: Taiwan: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

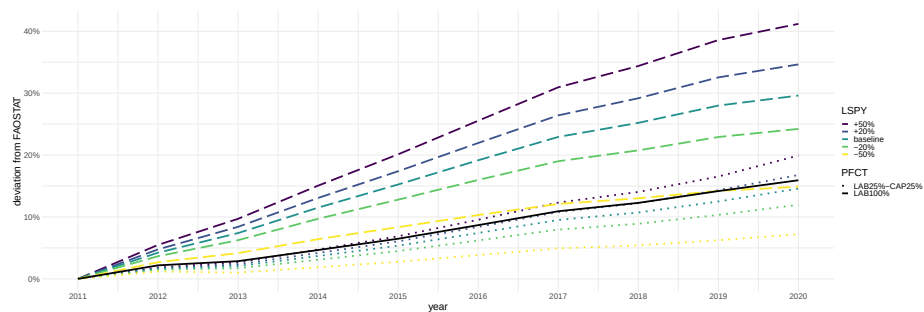


Figure 216: Tanzania: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

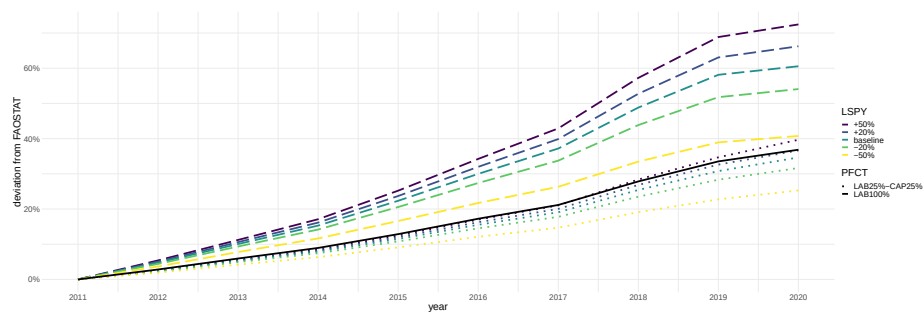


Figure 217: Uganda: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

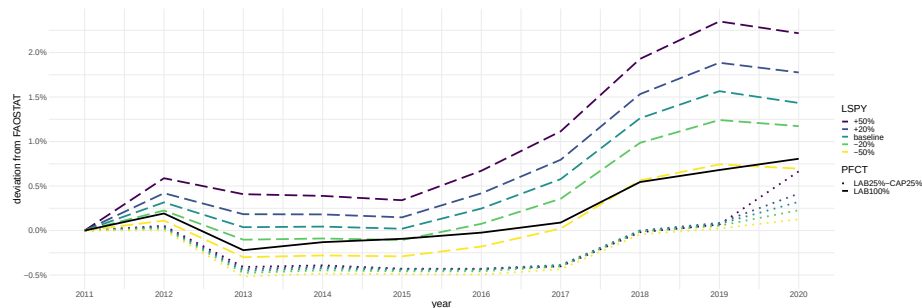


Figure 218: Ukraine: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

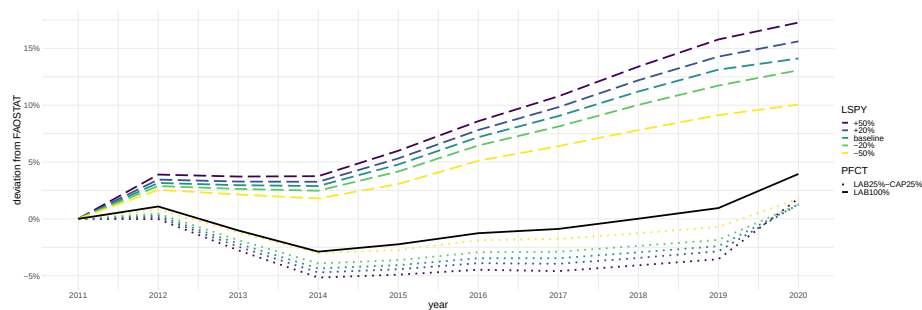


Figure 219: Uruguay: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

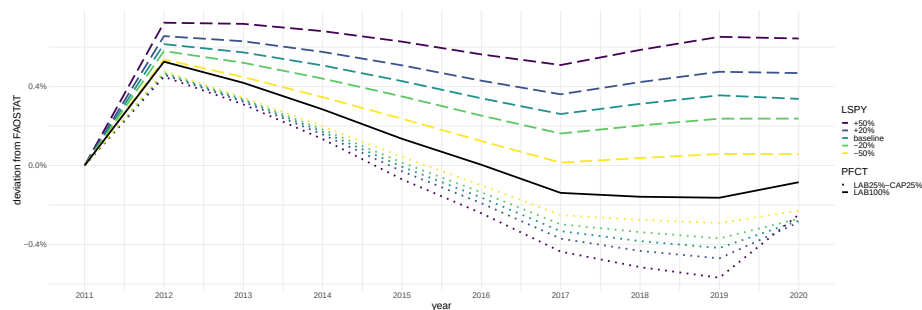


Figure 220: United States of America: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

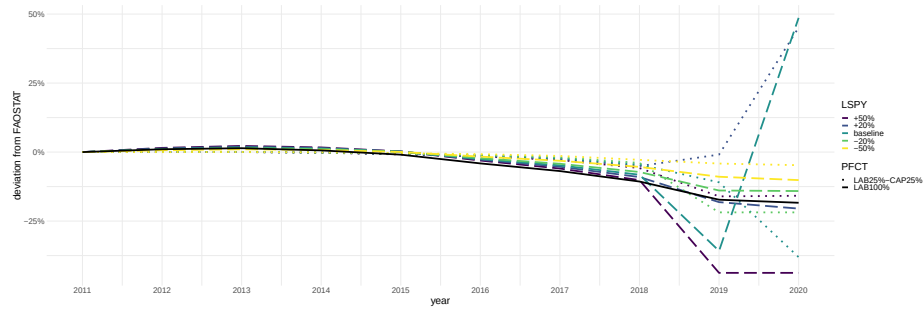


Figure 221: Venezuela: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

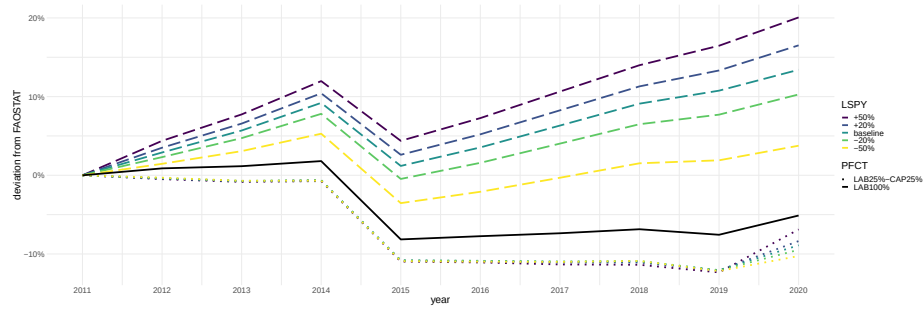


Figure 222: Viet Nam: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

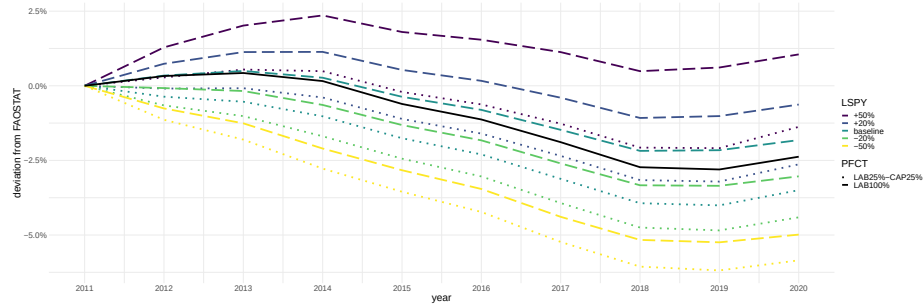


Figure 223: South Central Africa: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

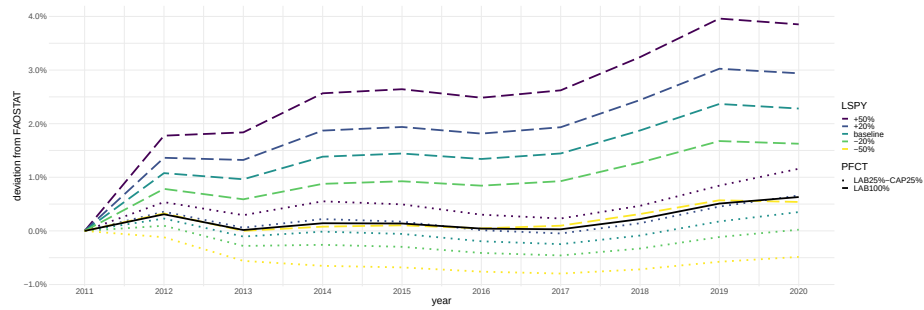


Figure 224: Central Africa: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

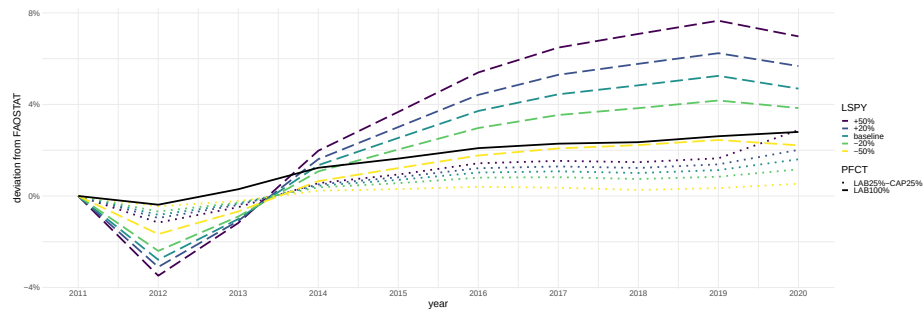


Figure 225: Rest of Eastern Africa: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

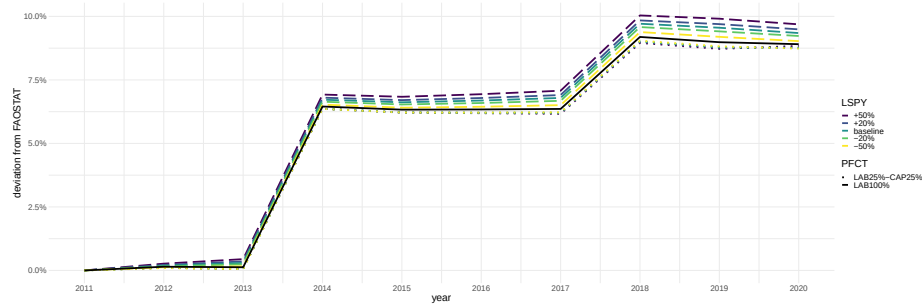


Figure 226: Rest of Eastern Europe: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

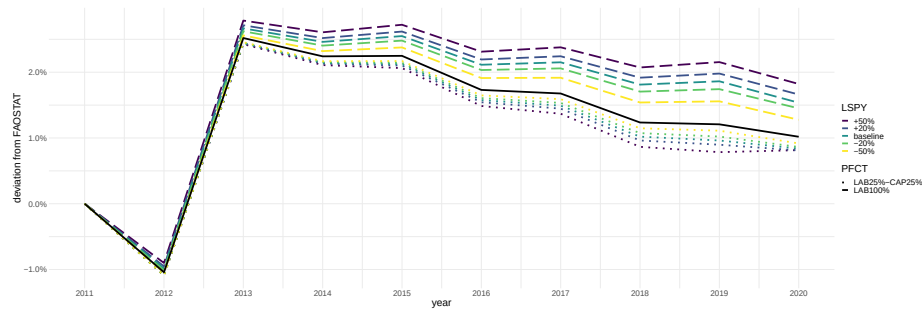


Figure 227: Rest of Europe: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

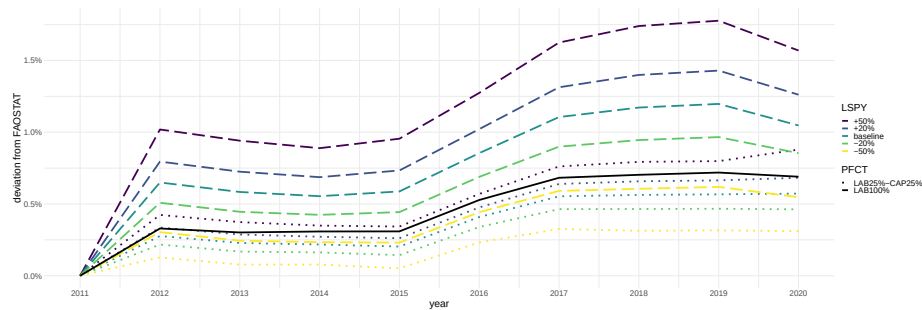


Figure 228: Rest of North Africa: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

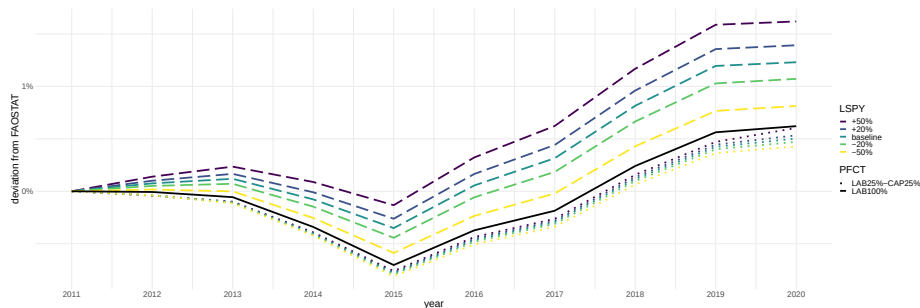


Figure 229: Rest of Oceania: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

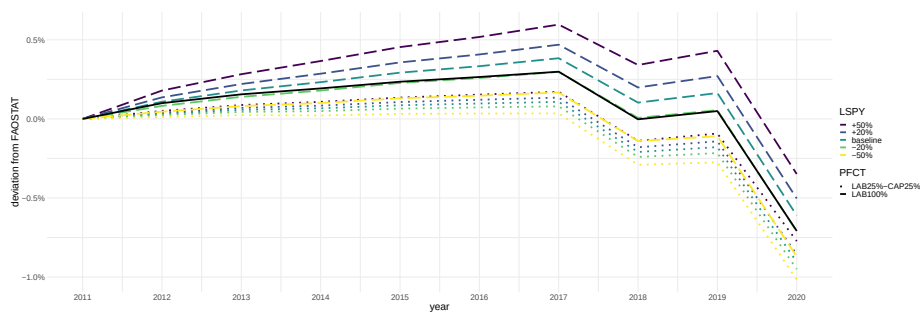


Figure 230: Rest of South Asia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

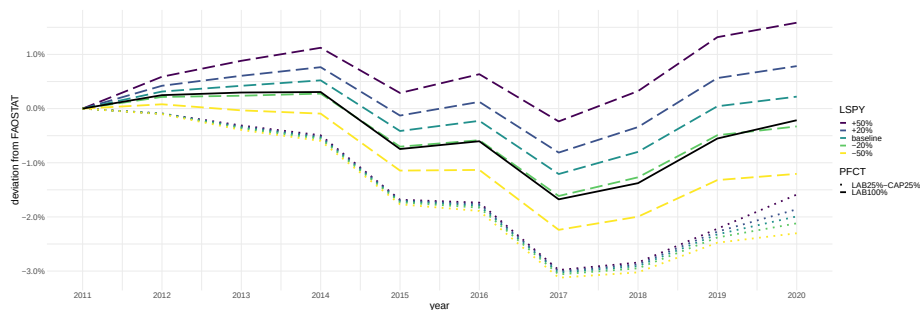


Figure 231: Rest of Southeast Asia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

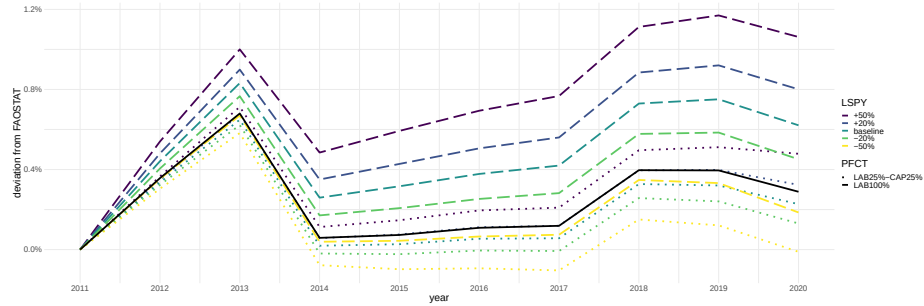


Figure 232: Rest of Central Asia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

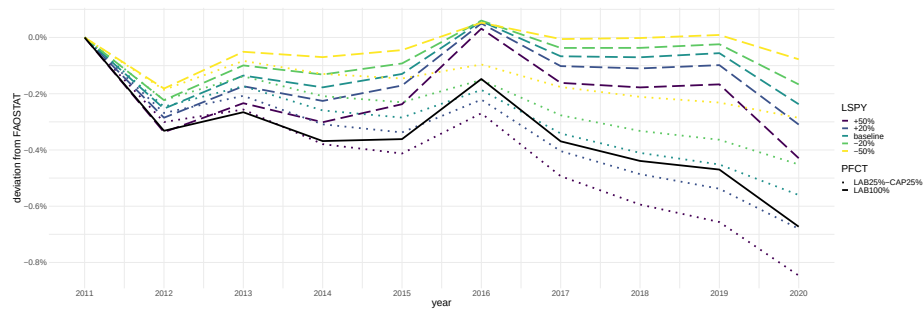


Figure 233: Rest of the World: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

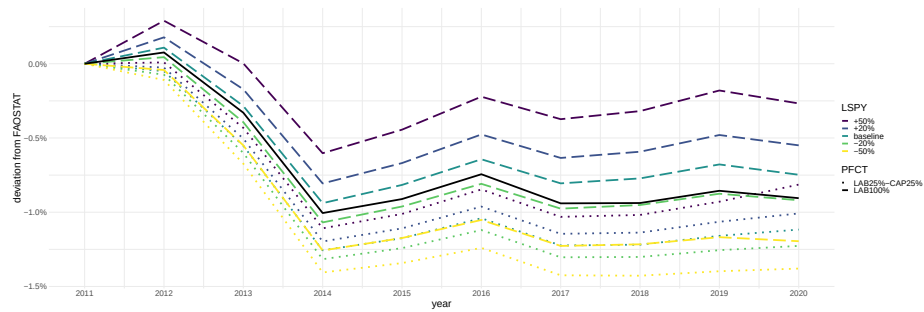


Figure 234: Rest of Western Asia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

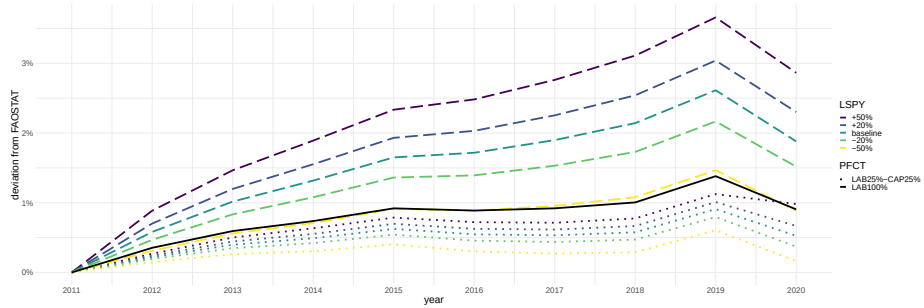


Figure 235: South Africa+: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

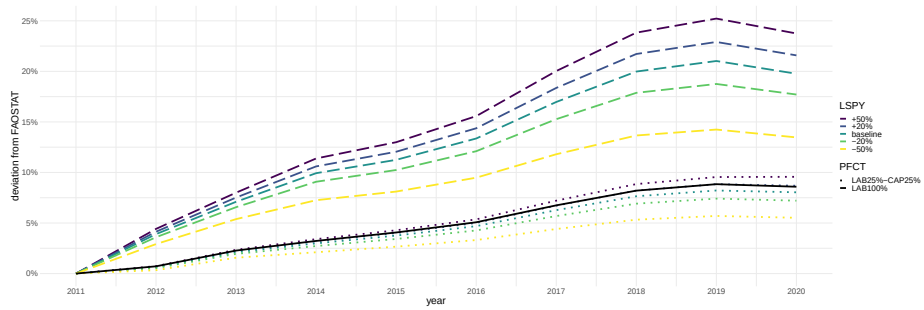


Figure 236: Zambia: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

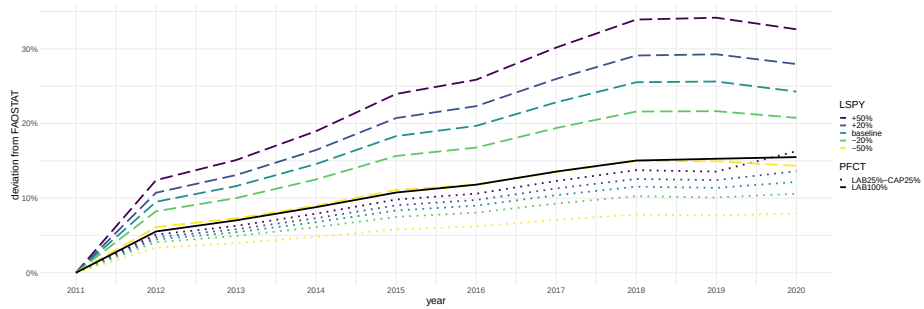


Figure 237: Zimbabwe: agricultural land deviation by land supply elasticity level (LSPY) and primary factor shocks (PFCT, percentage of GDP shock). Solid black line represents final hindcasting run.

6.5. Labor supply designation by study region

Table 8: Labor supply specification (percent of GDP shock)

study.name	labor supply
Albania	25%
Argentina	25%
Australia	25%
Austria	25%
Belgium	100%
Benin	25%
Burkina Faso	25%
Bangladesh	100%
Bulgaria	25%
Belarus	25%
Rest of Central America	25%
Bolivia	25%
Brazil	25%
Malaysia+	100%
Botswana	25%
Canada	25%
Caribbean	100%
The Caucasus	25%
Switzerland	25%
Chile	25%
China	25%
Cote d'Ivoire	25%
Cameroon	25%
Colombia	100%
Costa Rica	25%
Cyprus	100%
Czech Republic	100%
Germany	25%
Denmark	25%
Rest of East Asia	25%
Ecuador	25%
Egypt	100%
Spain	25%
Estonia	100%
Ethiopia	25%
Finland	25%
France	25%
United Kingdom	100%
Ghana	25%
Guinea	25%

Greece	25%
Honduras	25%
Croatia	100%
Hungary	25%
Indonesia	100%
India	25%
Ireland	25%
Iran Islamic Republic of	100%
Israel	100%
Italy	25%
Jordan	100%
Japan	25%
Kazakhstan	25%
Kenya	25%
Korea	25%
Kuwait	25%
Lithuania	100%
Luxembourg	100%
Latvia	100%
Rest of Western Africa	25%
Madagascar	25%
Mexico	25%
Malta	25%
Mozambique	25%
Mauritius	25%
Malawi	25%
Namibia	25%
Nigeria	25%
Nicaragua	25%
Netherlands	25%
Rest of EFTA	25%
New Zealand	25%
Pakistan	100%
Panama	25%
Peru	25%
Petrol States	100%
Philippines	25%
Poland	25%
Portugal	100%
Paraguay	25%
Romania	25%
Russian Federation	25%
Rwanda	25%
Saudi Arabia	25%
Senegal	25%
Singapore	100%

El Salvador	25%
Slovakia	25%
Slovenia	25%
Sweden	25%
Togo	25%
Thailand	100%
Tunisia	25%
Turkey	25%
Taiwan	25%
Tanzania	25%
Uganda	25%
Ukraine	25%
Uruguay	25%
Puerto Rico	25%
Venezuela	100%
Viet Nam	25%
South Central Africa	100%
Central Africa	25%
Rest of Eastern Africa	25%
Rest of Eastern Europe	25%
Rest of Europe	25%
Rest of North Africa	25%
Rest of Oceania	25%
Rest of South Asia	100%
Rest of Southeast Asia	100%
Rest of Central Asia	25%
Rest of the World	100%
Rest of Western Asia	100%
South Africa+	25%
Zambia	25%
Zimbabwe	25%