The role of global agricultural market integration in multiregional economic modeling: using hindcast experiments to validate an Armington model

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Abstract

The representations of international trade and global market integration play central roles in long-term global agricultural economic modeling. However, the conventional use of the gravity models (i.e., the Armington approach) of trade may not adequately account for the dynamic process of market integration. In this paper, we generalize a logit-based Armington approach by permitting home preference bias erosion to account for a trend of global market integration. We build a simple agricultural economic equilibrium model and conduct hindcast experiments to examine the historical trend of market integration. The results show a significant integrating trend of the global agricultural market implied by converging Armington preference distributions (i.e., home bias erosion) in 1995 – 2015, with a half-life of 44 years. We demonstrate important implications of allowing the dynamic trend of market integration implied by bias erosion on estimating trade elasticities. By testing the future market integration trend implied by historical home bias integration in GCAM, we show a high sensitivity of long-term agroeconomic projections to future trade and market integration scenarios.

JEL classifications: C61; F15; F18; Q17; Q56

Keywords: hindcast validation; home bias erosion; market integration; Armington; agricultural trade

1. Introduction

Multiregional multisectoral economic equilibrium models have been prominently used in the past two decades for providing economy-wide projections and understanding global and regional consequences of external shocks (e.g., changes in policy, productivity, environment, etc.) (Dellink et al., 2020; Hertel et al., 2016; van Tongeren et al., 2017). These economic models of human behaviors, when integrated with earth's systems and other biophysical responses, have become widely used for evaluating long-term social economic and climate scenarios (Calvin et al., 2019; Dissanayake et al., 2019; Moore et al., 2017; Nelson et al., 2014a; Porfirio et al., 2018; Riahi et al., 2017). At the core of these global economic models is the representation of international trade, which stipulates the interdependency of regional supply and demand and depicts economic geography (Bekkers et al., 2020; Robinson et al., 2014). However, an essential criticism of these models is that the commonly used gravity-based trade representation (e.g., the Armington approach) may not adequately account for the dynamic process of market integration. That is, they fail to capture the faster growth in trade relative to consumption or GDP[1], i.e., the so-called "missing globalization" issue (Van der Mensbrugghe, 2005; Yilmazkuday, 2017), and, thus, tend to underestimate the gains from market integration (Donaldson, 2015).

Global agricultural markets became increasingly integrated in the past two centuries, following the long-term trend of industrialization, globalization, and trade costs and barriers reduction (Coclanis, 1993; Coclanis, 2003; Donaldson, 2015). For robust trade modeling, a consideration of the dynamic process of market integration is crucial to improving projections of global and regional economics and their linkage to biophysical systems. More importantly, properly accounting for market integration also enhances the validation of economic models, which has been one of the most pressing challenges suggested over the course of model developments and applications (Baldos and Hertel, 2013; Calvin et al., 2017b; Dixon and Rimmer, 2010a; Schmitz et al., 2014; Zhao et al., 2020b). Thus, this paper aims to develop a framework for validating a multiregional agricultural trade equilibrium model using hindcast experiments with a focus on exploring the trend and impact of global agricultural market integration.

Previous studies examined market integration by investigating the convergency to the law of one price (LOP) (García-Hiernaux et al., 2016; Li et al., 2018; Parsley and Wei, 2001). They

[1] For example, in 1995 – 2015, the international trade of major crops (i.e., corn, soybeans, wheat, and rice) increased by over 150%, much faster than the growth in these crops' total world consumption, about 60% in the same period (FAOSTAT, 2020). In the same period, the world population increased by 28% and GDP increased by 150%.

highlighted the important role of product heterogeneity and time (as market integration is a process rather than a condition) in explaining price differences across supplying sources (Goodwin et al., 1990; Pippenger and Phillips, 2008; Thursby et al., 1986). When it comes to global economic modeling, particularly with consumer prices varying by origin, the Armington approach is usually employed to explain the price differentiation with the heterogeneity in consumer preference (Armington, 1969). That is, consumers view goods produced in different origins as imperfect substitutes. The Armington approach, providing a theoretical foundation for the gravity relationship (Anderson and van Wincoop, 2004), has been widely used in empirical trade modeling (Bekkers et al., 2020). However, the conventional use of the Armington approach may not account for the dynamic process of market integration (or segmentation) since the parameters reflecting the relative preferences (or namely "tastes") of products across origins are usually assumed to be independent of time or shocks (Hillberry et al., 2005).

As a standard assumption in economic equilibrium models, the Armington approach calibrates preference parameters to reproduce observations (i.e., bilateral trade flows and prices) in a base year. These parameters capture the preference bias in consumption, usually towards locally produced products (i.e., home bias) (Whalley and Xin, 2009). Hillberry et al. (2005) interpreted the Armington preference parameters as econometric residuals. They found that, for the 33 commodity groups assessed using a base year of 1995, these parameters explained 80 percent of variations in bilateral trade flows. That is, trade patterns are largely determined by the fixed preference parameters in Armington models. What factors do the Armington preference parameters encompass? Common factors that demonstrated statistical success in gravity models include distance, language, and adjacency (border effect)[2] (Anderson and van Wincoop, 2004; Caliendo and Parro, 2014; Hertel et al., 2007). Even though these factors are fixed, their gravity, i.e., impacts on the bilateral relationship, could change over time (e.g., decreasing distance elasticity or weakening culture and border effects). Furthermore, preference parameters may also reflect other factors not directly explained by the model (Zhai, 2008), such as variety or quality difference (Feenstra, 1994; Hertel et al., 2007), imperfect information (Matveenko, 2020), and non-tariff barriers (Balistreri and Tarr, 2020; Grübler and Reiter, 2021; Jafari and Britz, 2018). These factors can be broadly viewed as unmeasured trade costs, and declines in such costs would reflect the homogenization of tastes or integration of markets (Anderson, 2011; Jacks et al., 2011). Liu et al. (2004) demonstrated such integration, termed erosion of home preference

[2] E.g., regions with shorter bilateral distance, similar languages, or cultures, and sharing a border tend to have higher "gravity" and thus trade more.

bias, in 1986 – 1995 and found more vigorous home bias erosion for developing countries than developed countries. Nevertheless, shocks on bilateral tastes, albeit the critical implications, have hardly been implemented in empirical studies, mainly due to the difficulty in developing plausible future exporter-specific scenarios (Hillberry and Hummels, 2013).

Considering market integration (or segmentation) implied by preference changes could be crucial for trade elasticity estimation and model validation. Recent studies also illustrated the high sensitivity of market integration assumptions for evaluating future scenarios by comparing the Armington approach with a Heckscher-Ohlin-Vanek (HOV) approach of fully integrated world markets (IWM) modeling (i.e., single world price) (Hertel and Baldos, 2016; Morey, 2016; Zhao et al., 2021). In this paper, we illustrate a dynamic reconciliation between the two approaches, in which Armington models of regional markets would approach IWM through eroding preference bias and easing product heterogeneity. In other words, we demonstrate a theoretical connection between Armington preference shocks and the dynamic process of market integration. We then examine the historical integration of global agricultural markets while calibrating trade elasticities with hindcast experiments.

The most common strategy of a historical validation is to draw model parameters from empirical time-series econometrics; see Ahmad et al. (2020) for a comparison of literature estimates of trade elasticities and Bajzik et al. (2020) for a meta-analysis. However, there are also concerns with the strategy, such as (1) spotty coverage of the elasticity parameters available in the econometric literature, (2) inconsistent mapping between econometrically estimated elasticities and parameters in parsimonious functions used in economic equilibrium models, and (3) partial econometric identifications without considering the full set of market equilibrium constraints (Arndt et al., 2002; Dixon and Rimmer, 2013). An alternative historical validation strategy is hindcast, in which the model is run over historical periods and results can be compared with observation data. Hindcast experiments were adopted as early as in the Norwegian model in Johansen (1960), though they became less popular in recent decades as models and required data became increasingly complicated (Dixon and Rimmer, 2010a).

Table 1 summarizes recent hindcast validation efforts. The summary is not exhaustive, while the efforts were drops in the bucket compared to the broad uses of the models. Most studies focused on evaluating the hindcast performance in one area of interest, e.g., bilateral trade flows (Gehlhar, 1996; Kehoe, 2005), agriculture and land use (Baldos and Hertel, 2013; Calvin et al., 2017b), or energy markets (Beckman et al., 2011; Fujimori et al., 2016). Several studies also examined sectoral-wide projections (Dixon and Rimmer, 2010b; Kehoe et al., 1995), though mostly focused on a single region except for Van Dijk et al. (2016). Hindcast experiments are instrumental in understanding how models perform given key assumptions and identifying areas for improvement (Calvin et al., 2017b). More importantly, they also offer opportunities for enhancing key modeling parameters, e.g., trade parameters in Liu et al. (2004) and energy demand parameters in van Ruijven et al. (2010), and examining alternative modeling assumptions and structures, e.g., R&D-based total factor productivity (TFP) growth in Hong et al. (2014) and imperfect foresight schemes in agricultural production Calvin et al. (2017b), based on tests of goodness-of-fit.

Table 1 Summary of studies performing hindcast experiments

Study	Study period & time step	Model	Validation focus
Kehoe et al. (1995)	1985 - 1987; 1 & 2-year	Country-level GE	Spain; all 12 sectors
Gehlhar (1996)	1982 - 1992; single	GTAP	Global (6 regions); export share of all 7 traded sectors
Arndt et al. (2002)	1992 - 1996; annual	Country-level GE	Mozambique; macroeconomics and trade
Liu et al. (2004)	1986 - 1995; 3-year	GTAP	Global (10 regions); trade volume of all 8 traded sectors
Kehoe (2005)	1988 - 1999; single	Global GE	Global; GDP-weighted trade flows
Guivarch et al. (2009)	2003 - 2006; annual	IMACLIM-R	Global (Indian-focused); GDP and sector output growth
van Ruijven et al. (2010)	1970 - 2003; annual	IMAGE/TIMER	Global; Transport & building
Dixon and Rimmer (2010b)	1998 - 2005; single	USAGE	USA; all 503 sectors
Beckman et al. (2011)	2001 - 2006; single	GTAP-E	Global; energy sectors
Baldos and Hertel (2013)	1961 - 2006; single	SIMPLE	Global; agriculture & land use
Chaturvedi et al. (2013)	1990 - 2010; 5-year	GCAM-USA	USA; building
Hong et al. (2014)	1995 - 2010; annual	Country-level GE	South Korea; outputs of 27 sectors
Van Dijk et al. (2016)	2001 - 2007; single	MAGNET	Global; all 22 sectors
Fujimori et al. (2016)	1981 - 2010; annual	AIM/CGE	Global; energy sectors
Calvin et al. (2017b)	1990 - 2010; annual	GCAM	Global; Agriculture & land use

In this paper, we build a 6 (crops) by 6 (regions) agricultural economic equilibrium model with bilateral trade. We leverage the logit-based Armington approach developed in Zhao et al. (2021), which provides an explicit definition of preference parameters following a discrete choice modeling framework. We develop market integration scenarios to allow Armington preference distributions to change over time. From running hindcast experiments using the simple model over 1995 – 2015 (with 5-year steps) with parameter optimization, the results demonstrate a significant integrating trend of the global agricultural market implied by converging preference distributions (i.e., home bias erosion) over time. In addition, we examined home bias erosion trends in a well-established model, Global Change Analysis Model (GCAM), and demonstrated important trade and land use implications in long-term agroeconomic projections.

The rest of this paper is organized as follows. In **Section 2**, we develop the theoretical model and the market integration scenario that generalized the Armington approach to allow home bias erosion. The hindcast framework is also outlined. In **Section 3**, the empirical model and data for hindcast experiments are described, along with the scenarios to be investigated. The hindcast optimization results are provided in **Section 4,** and the implications of future market integration are discussed in **Section 5**. Finally, **Section 6** concludes the study.

2. Theory and quantitative implications

2.1. Theoretical model

This study employs the logit-based Armington approach developed in Zhao et al. (2021)[3]. Unlike the constant elasticity of substitution (CES) function conventionally used for aggregating products from different origins, the logit-based Armington approach provides a probabilistic representation of consumer preference, based on the widely used discrete choice modeling framework (Clarke and Edmonds, 1993; Eaton and Kortum, 2002; McFadden, 1973; Zhao et al., 2020a). In particular, consumers shop around the world to buy from a source with the lowest preference-adjusted price. The probability that source i offers the lowest preference-adjusted price is also the volume share of the good that the country purchases from source i. Assuming the preference parameters follow independent Weibull distributions[4] (Type III extreme value) with parameters (T_i, θ), the bilateral demand (Q_i, with home region index omitted) by source can be derived as

$$Q_i = \frac{P_i^{-\theta} T_i^{\theta}}{\sum_k P_k^{-\theta} T_k^{\theta}} Q, \tag{1}$$

where Q is the aggregate demand in a region, P_i are consumer prices by source, T_i are scale parameters (logit share-weights) representing the unconditional mean of the preference distributions, and θ is a positive shape parameter (logit exponent) providing an inverse measure of preference heterogeneity. In contrast to the CES-based Armington, the logit-based Armington approach relies on physical trade flows and provides a more explicit definition of preference parameters. Here, with the logit-based Armington approach, we extend the conventional

[3] The development of the Logit-based Armington trade modeling approach from Zhao et al. (2021) is provided in SI with permissions from the authors.

[4] Cumulative distribution function: $F_i(z) = 1 - e^{-\tilde{\gamma}^{-\theta}(T_i z)^{\theta}}$, where $\tilde{\gamma} = [\Gamma(1 + \theta^{-1})]^{-1}$ where $\Gamma(\cdot)$ is Gamma function.

theoretical model (e.g., Hertel and Tsigas (1996) and Warr (2008)) to illustrate price transmission between international and domestic prices and to demonstrate the crucial role of preference distribution parameters in describing a path to fully integrated market.

Equation 1 can be translated to its linearized form for domestic and import demand, shown in equations 2 and 3, respectively.

$$q_d^D = q^D + \theta S_m(p_m - p_d) - \theta S_m(t_m - t_d) + S_m \ln\left(\frac{S_d}{S_m}\right)\hat{\theta} \quad (2)$$

$$q_m^D = q^D + \theta S_d(p_d - p_m) - \theta S_d(t_d - t_m) + S_d \ln\left(\frac{S_m}{S_d}\right)\hat{\theta} \quad (3)$$

Lower case letters represent proportional changes, e.g., q^D (superscript D denotes demand) denotes the proportional change in aggregate demand, and q_d^D and q_m^D (subscript denotes source) denote proportional changes in domestic and import demand, respectively. S_d and S_m are volume shares in consumption. Also, t_i and $\hat{\theta}$ are proportional changes in preference parameters (T_i) and logit exponent (θ, implying trade elasticity), respectively. Since $t_i = \hat{\theta} = 0$ in previous studies, the related terms were usually omitted. However, changes in the preference distribution parameters could notably shift demands. In particular, an increase in relative preference parameters (e.g., $t_m - t_d$) would shift demands toward a favored source (e.g., q_m^D) while an increase in $\hat{\theta}$ would encourage a relatively higher demand for the source with a larger initial consumption share. Note that the initial preference parameters, T_i , are calibrated based on θ and S_i so that they did not play any roles in the trade responses (equations 2 and 3). In contrast, both the initial Armington elasticity, θ, and its changes, $\hat{\theta}$, are factored into the trade responses.

The aggregate demand, equation 4, is a function of own price (p), cross-price (p_o), and expenditure (e), in proportional changes,

$$q^D = \eta^D p + \varphi^D p_o + \phi e, \quad (4)$$

where η^D, φ^D, and ϕ denote own-price, cross-price, and income elasticities, respectively. The linkage to the composite price, p, is derived from the zero-profit condition,

$$p = V_m(p_m + q_m) + V_d(p_d + q_d) - (S_m q_m + S_d q_d), \quad (5)$$

where V_d and V_m are value shares in consumption by source. This simple partial equilibrium model of trade can be closed with market clearing conditions linking demands respectively to domestic and international supply, i.e., $q_d^S = \xi_d^S(p_d - \tau_d)$ and $q_m^S = \xi_m^S(p_m - \tau_m)$. ξ_d^S and ξ_m^S are supply elasticities for domestic and international products, and τ_i are proportional changes in ad valorem price wedge, i.e., including tariffs and transport margins, between producer and consumer prices.

Solving the theoretical model, the elasticity of price transmission ($H_m \leq 1$) between international and domestic prices, or the pass-through elasticity is derived (equation 6).

$$H_m = \frac{\eta^D \xi_m^S (V_m - S_m) + \eta^D V_m + \theta S_m}{\xi_d^S - \eta^D + \eta^D \xi_d^S (V_m - S_m) + \eta^D V_m + \theta S_m} \quad (6)$$

H_m is an increasing function of θ. It is important to note that when θ increases (towards infinity), H_m approaches a full price transmission ($H_m = 1$) and the calibrated relative preference parameters (T_i/T_j) would approach the initial price ratio (P_i/P_j). Therefore, under a fully IWM featured by full price transmission ($\theta = \infty$) and homogeneous prices ($P_i/P_j = 1$), preference parameters would be equal ($T_i/T_j = 1$). In other words, the Armington approach can be generalized to an IWM with homogeneous products (i.e., HOV) by stipulating a dynamic trend of increasing θ and converging T_i.

2.2. Market integration scenarios

In the Armington approach, the preference distributions are calibrated given θ and initial market equilibrium. **Fig. 1** illustrates the calibration and trade responses using an example of soybeans consumption in Asia. Initial data play a crucial role in determining preference distributions and trade responses. When $\theta = 3$, the calibration indicates that there was a preference bias towards soybeans produced in Asia (i.e., $T_{domestic}/T_{imported} = 1.7 > 1$) in 1995 (see **Fig. S1**), and such home bias would be carried overtime under conventional assumptions. In our study, following the theoretical intuition provided in **Section 2.1**, we generalize the Armington approach to permit market integration implied by dynamic changes in preference distributions. In particular, we develop two market integration scenarios: (1) bias erosion and (2) full homogenization.

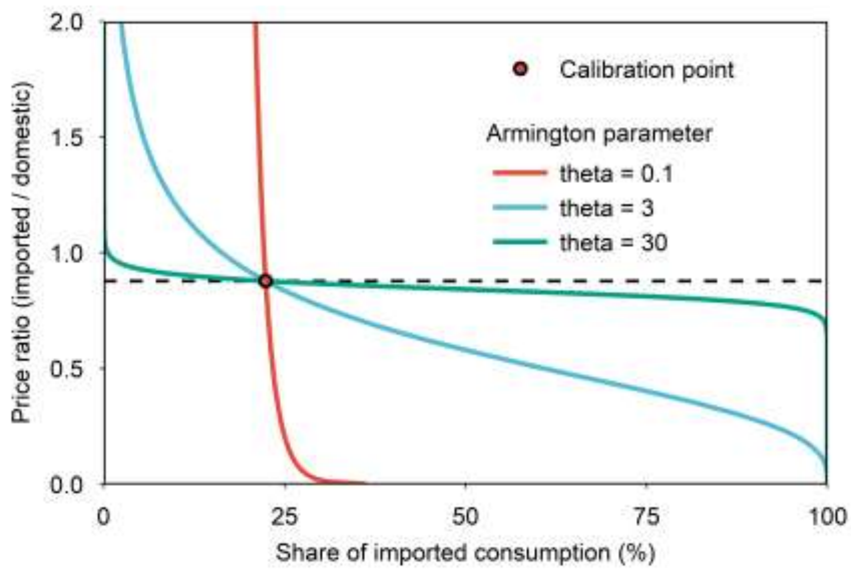

Fig. 1 Calibration and trade responses in the Armington approach. Curves represent responses of volume share of imported product in the total consumption with respect to the price ratio between imported and domestic products with different magnitude of parameters (θ). The figure is generated using data of 1995 Asian soybeans consumption and price data, in which imported soybeans accounted for 22% of the total soybeans consumption in Asia.

In the bias erosion scenario, we allow preference distributions to shift, i.e., shocks on $T_{i,n}$ in period n. In particular, we introduce a rate of relative convergence, δ_n ($\delta_0 = 1$), to govern the relative shift in preference distributions (equation 7). When $\delta_n > 1$, preference distributions converge relative to period 0. It indicates reductions of preference bias implied trade barriers so that consumers become more equally accessible to markets of different origins and, thus, the world market is increasingly integrated. In contrast, when $\delta_n < 1$, it indicates a process of market segmentation. Furthermore, the half-life of the convergence rate, calculated as $\ln(2)/\ln(\delta_n)$, can be used to measure the number of periods it takes to reach half of the market integration effect from a full preference bias erosion (Li et al., 2018).

$$T_{i,n} = T_{i,0}^{\frac{1}{\delta_n}} \tag{7}$$

In the full homogenization scenario, we also allow the preference distribution to scale, i.e., shocks on θ_n in period n, in addition to shifts in the bias erosion scenario. However, it is important to note that, unlike shock on $T_{i,n}$, shocks on θ_n, an inverse measure of product heterogeneity, alone do not have market integration implications, and its responses are heavily contingent on other shocks and markets. That is, trade responses could be inconsistent from between shocks on $T_{i,n}$ and θ_n. Thus, we add such a scenario for testing purpose, and we stipulate an illustrative connection between δ_n and θ_n shocks, i.e., $\delta_n = \theta_n/\theta_0$. Such a tie between δ_n and θ_n is essential to avoid over identifications in the hindcast optimization and to have a fair comparison between integration scenarios. That is, preference distributions would shift with changes in the Armington exponent parameter. If θ_n increases over time, along with market integration implied by bias erosion ($\delta_n > 1$), markets may become more integrated since products are more homogeneous to consumers, and trade is more responsive to prices.

The two market integration scenarios of preference distribution shocks are compared in **Fig. 2** for their price responses to comparative static preference shocks in the theoretical model with base data of Asian soybeans in 1995. Under the bias erosion scenario, demand from the source biased against (imported soybeans in this case) would increase, which encourages a higher relative price of this source. However, under the scenarios of full homogenization, the price ratio would approach one with the preference shocks, whereas the point of homogeneous prices ($P_i/P_j = 1$) and preferences ($T_i/T_j = 1$) represent the fully IWM. It is also important to note that despite the theoretical linkage to IWM in the full homogenization scenario, the implied integration path may not necessarily be supported by data as the fully IWM itself is not empirically realistic. Under the conventional assumption of no preference shocks, both price ratio and preference parameter ratio would remain unchanged (at the calibration points) in the case. We investigate whether the market integration scenarios would perform better than the conventional scenario of no preference shock implied integration with hindcast experiments.

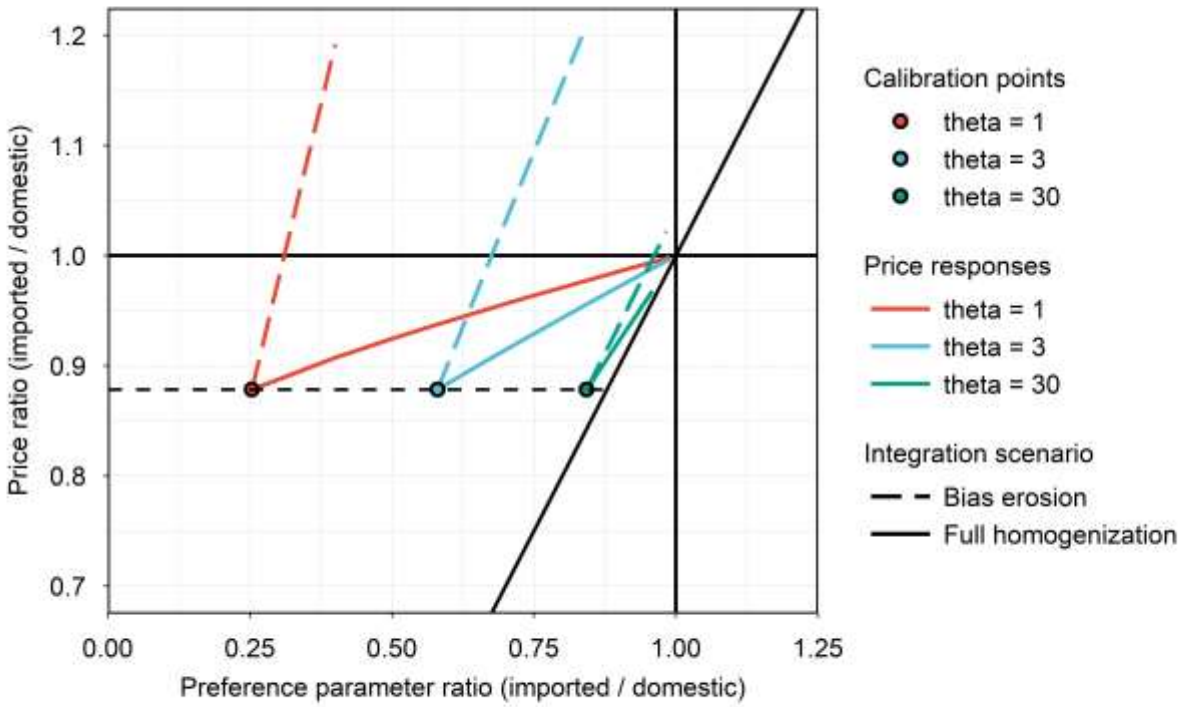

Fig.2 Price responses to comparative static preference shocks across market integration scenarios. The calibrations points show the relationship between initial price ratio and calibrated preference parameter ratio given an initial theta (θ_0). Note that the diagonal black is 45-degree line. Lines (distinguished by integration scenarios) are simulated by implementing comparative static shocks of δ_n (bias erosion scenario) or θ_n (full homogenization scenario) in the theoretical model (**Section 2.1**). The theoretical model is calibrated to 1995 Asian soybeans data for different initial theta (θ_0 equals 1, 3, or 30) with other parameters of $\eta^D = -0.5$, $\xi_d^S = \xi_m^S = 0.5$, and $p_o = e = 0$.

2.3. Hindcast and goodness-of-fit

The system of equations that represents the economic equilibrium of year n can be written as

$$\mathbf{F}(\mathbf{X}_n, \mathbf{Z}_n, \boldsymbol{\theta}_n, \mathbf{T}_n, \mathbf{B}) = \mathbf{0} \tag{8}$$

where $\mathbf{X}_n$ is a vector of endogenous variables such as prices and quantities, $\mathbf{Z}_n$ is a vector of exogenous shocks, $\boldsymbol{\theta}_n$ and $\mathbf{T}_n$ are vectors of logit exponent and share-weight parameters, respectively, in the logit-based Armington trade modeling, and $\mathbf{B}$ is a vector of other behavior parameters required in the model (Arndt et al., 2002). In hindcast experiments, the model is run across historical periods. Given vectors of historical shocks and assumed behavior parameters, the model can be solved with a closed-form solution with numerical procedures, i.e., $\mathbf{X}_n =$

$\mathbf{F^{-1}}(\mathbf{Z}_n, \boldsymbol{\theta}_n, \mathbf{T}_n, \mathbf{B})$. Thus, a vector of errors ($\boldsymbol{\varepsilon}_n$) is the difference between the observed data ($\mathbf{X}'_n$) and the estimates ($\mathbf{X}_n$).

$$\mathbf{X}'_n = \mathbf{F^{-1}}(\mathbf{Z}_n, \boldsymbol{\theta}_n, \mathbf{T}_n, \mathbf{B}) + \boldsymbol{\varepsilon}_n \quad (9)$$

In an initial period ($n = 0$), $\mathbf{T}_0$ is calibrated given $\boldsymbol{\theta}_0$ and base data so that $\mathbf{X'}_0 = \mathbf{F^{-1}}(\mathbf{Z}_t, \boldsymbol{\theta}_0, \mathbf{T}_0, \mathbf{B})$ and $\boldsymbol{\varepsilon}_t = \mathbf{0}$. By comparing $\boldsymbol{\varepsilon}_n$ across different dimensions, modelers can identify areas for further investigations and improvements. The model performance against historical observations can be evaluated based on measures of goodness-of-fit, e.g., bias (Baldos and Hertel, 2013; Chaturvedi et al., 2013), mean absolute error (MAE) (Hong et al., 2014; Van Dijk et al., 2016), root mean square error (RMSE), mean absolute percentage error (MAPE) (Fujimori et al., 2016), and root mean square percentage error (RMSPE) (van Ruijven et al., 2010). Different goodness-of-fit measures essentially put different weights on different error points in an aggregated measure. Dixon and Rimmer (2010b) and Kehoe et al. (1995) also considered explicitly adding weights directly in the measurement. See Snyder et al. (2017) for further discussions of different goodness-of-fit measures.

This study uses a weighted mean square logarithmic error (WMSE) to simultaneously measure goodness-of-fit of both prices and quantity (equation 10). WMSE measures weighted mean squared "distance" between estimated and observed market equilibriums across market m and period n. The logarithmic difference provides a unitless relative measure of error. The weights ($W_{m,n}$) are further discussed in **Section 3**.

$$\mathrm{WMSE} = \sum_n W_n \sum_m W_{m,n} \left[\left(\ln P_{m,n} - \ln P'_{m,n} \right)^2 + \left(\ln Q_{m,n} - \ln Q'_{m,n} \right)^2 \right] \quad (10)$$

3. Empirical modeling and experiments

We extend the theoretical model of bilateral trade described in **Section 2.1** to build a simple global agricultural economic equilibrium model. The model includes six regions, separating the world by continents (i.e., Africa, Asia, Europe, North America, South America, and Oceania), and six crops (i.e., corn, wheat, rice, soybeans, rapeseed, and an aggregated other crop). Crop production in each region has land rental and nonland costs. The logit approach is used for land use transformation (Wise et al., 2014; Zhao et al., 2020a). The CES utility function is used for crop consumers in addition to an exogenous crop demand shock for biofuel mandates. Also, following the literature convention (Hertel et al., 2007), a two-level nested structure of the logit-based Armington approach is employed to first aggregated imported crops across different sources and then nest the composite of imported crops with the domestically produced crop. This model's exogenous variables include crop yields, nonland costs, biofuel mandates, and bilateral transport margins and tariffs. The endogenous variables include crop harvested area, production, consumption, bilateral trade, and prices for all crops and regions. The model is similar to a simplified version of the agriculture and land use (AgLU) module of the GCAM (Calvin et al., 2017b; Zhao et al., 2020a), but with bilateral crop trade.

We employ data for crop production, land use, prices, bilateral trade volume and transport margin, and crop consumption for biofuels from the Food and Agriculture Organization (FAO) and the Organization for Economic Co-operation and Development (OECD) databases (FAOSTAT, 2020; OECD and FAO, 2020) and draw production cost and tariffs data from the GTAP Data Base (Aguiar et al., 2016). Where appliable, 5-year average data are used. Thus, we assemble a dataset representing global agricultural trade equilibrium from 1995 – 2015, with 5-year intervals (see **Supplementary Information (SI) Figs. S2 – S3** for visualization of historical bilateral trade data). The dataset and the model are built in an R project and are publicly available.

The model is purposely designed simply in this study to reduce computational burdens in optimization and to make the results easy to communicate. In the hindcast experiments, we use the base year of 1995 by default and simulate more recent years. We also set the total cropland supply and the total expenses of crop consumption exogeneous and use the uniform behavior parameters across regions. We use 1 for the CES demand parameter and -1 for the land supply logit exponent and test their sensitivity (Gouel and Laborde, 2018; Zhao et al., 2020a). The Armington parameters (logit exponents), both in domestic – foreign (θ^D) and foreign – foreign (θ^M) nests, are also assumed to be uniform across regions and crops. Note that the market integration scenarios tested in this study focus on the domestic – foreign nest, i.e., home bias erosion.

With hindcast experiments, we compare four scenarios, i.e., S0 – S3 described in **Table 2**. Scenario S0 follows conventional assumptions of fixed initial preference distributions and uses literature Armington parameters for crops (Hertel et al., 2007). Scenario S1 uses Armington parameters estimated specifically for our model in the optimization. Scenarios S2 and S3 incorporate the two market integration scenarios developed in **Section 2.2** into the top nest of the Armington structure in our model to allow changes of market integration parameters (δ_n or θ_n^D). In S1 – S3, parameters are optimized by minimizing WMSE (equation 10). There are up to 6 (importing regions) x 6 (exporting regions) x 6 (crops) = 216 markets in each period. **Fig. 3** shows the path of changing bilateral regional market equilibrium across the 5 study periods using examples of soybean markets. Minimizing WMSE is effectively minimizing the weighted mean distance between estimated and observed market equilibriums across all markets and the four projection periods. We use consumption shares as weights across periods (W_n), and the shares of the square root of trade (or consumption) volume as cross-sectional weights ($W_{m,n}$). Note that the errors are weighted as the model would predict larger errors (in relative terms) for small bilateral trade flows. Also, the observed bilateral trade flows are scaled using square root to normalize the weights. Several major consumption flows could otherwise dominate the parameter estimates. The logarithmically scaled volume weights were also tested in the sensitivity analysis (see **Figs. S4 – S6** for a comparison of weights).

Table 2 Experimental design

Scenario	Integration scenario	Preference shock	Parameter	Description
S0	No integration	Fixed preference distributions	$\theta^D = 3$ and $\theta^M = 6$	Fixed initial preference bias with literature parameters.
S1	No integration	Fixed preference distributions	θ^D and θ^M from optimization	Fixed initial preference bias with optimized parameters.
S2	Bias erosion	Shift of Armington preference distributions	θ^D, θ^M, and year-specific δ_n from optimization	Market integration through home bias erosion if $\delta_n > 1$.
S3	Full homogenization	Shift & scale of Armington preference distributions	θ_0^D, θ^M, and year-specific θ_n^D from optimization (with constraints of $\delta_n = \theta_n/\theta_0$)	Market integration through both home bias erosion and product homogenization if $\theta_n^D > \theta_0^D$.

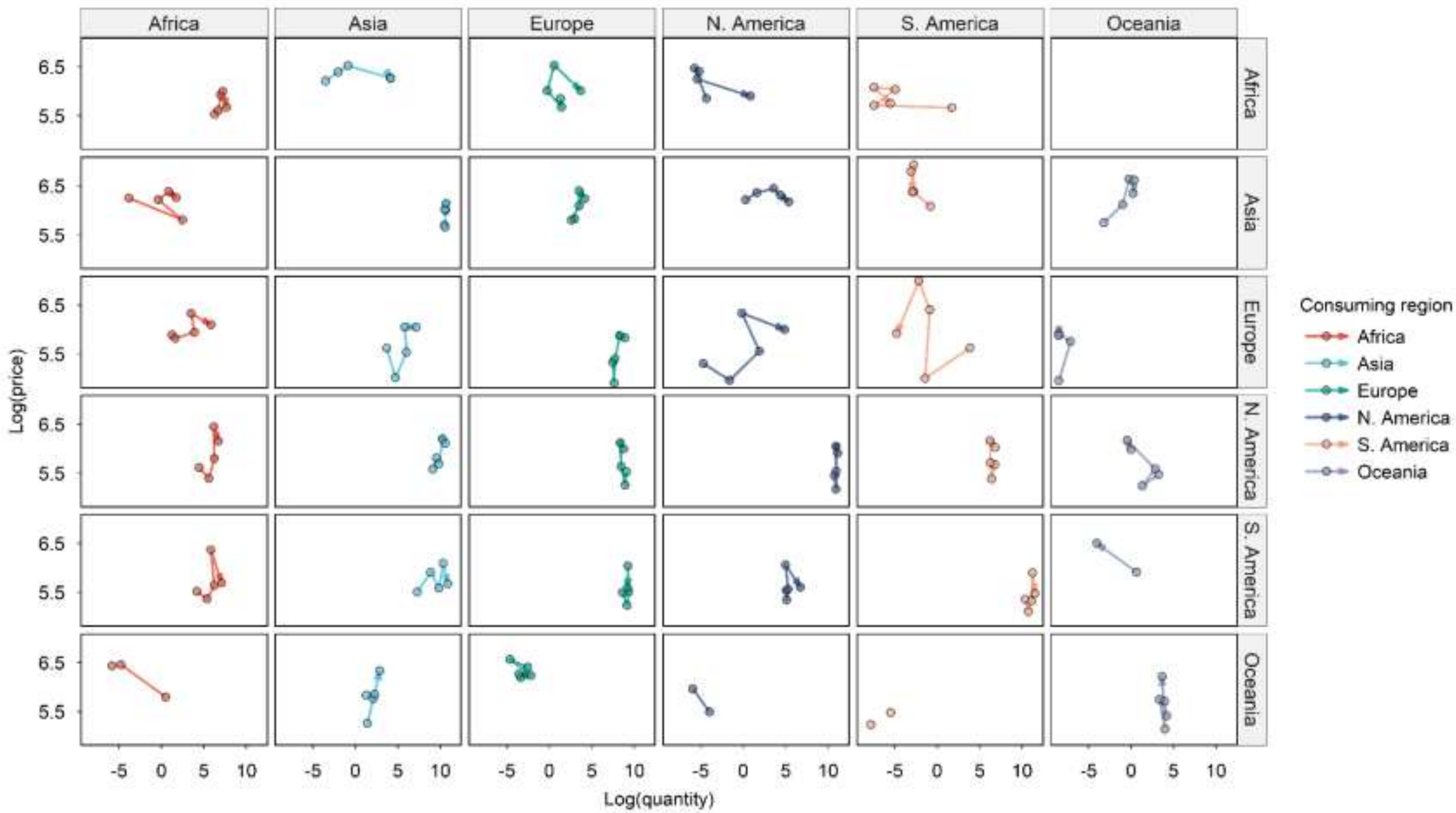

Fig. 3 Bilateral regional market equilibrium of soybeans for consuming regions (columns) across sources (rows). Points represent market equilibriums (natural logarithm of price and quantity) of 5 periods, 1995 – 2015 with 5-year interval. Lines (with arrow) connects the market equilibriums in chronological order. Note that diagonal plots show domestic market equilibrium. Bilateral market equilibrium does not necessarily exist for all periods. For example, Oceania does not import soybeans from Africa.

4. Results

4.1. Market integration in hindcast experiments

A comparison of estimated parameters from the hindcast optimization across market integration scenarios is presented in **Table 3**. **Fig. 4** compares bilateral trade volume shares in 2015 across the scenarios (trade volumes shown in **Fig. S6**). Relying on literature Armington parameters and assuming no preference implied integration, scenario S0 reported a WMSE of 1.351. By using θ^D and θ^M that minimize WMSE in the hindcast experiment, the model was significantly improved as WMSE decreased to 0.577 in S1. When allowing shifts in preference distributions with rates of δ_n, the model in S2 was further improved compared with S1 as WMSE decreased to 0.495. Notably, the integration parameters, δ_{2000} – δ_{2015} were significantly greater than one, which indicated home bias erosions relative to the base year of 1995. The gradually increasing δ_n also implied a trend of global agricultural market integration through eroding home bias over the study periods. In contrast, in the illustrative scenario of full homogenization (S3), the results did not indicate a clear trend of θ_n^D or the tied δ_n, as driven by the expected inconsistent market responses between the shocks of θ_n^D and δ_n (discussed in **Section 2.2**). The WMSE in S3 was also larger than S2.

Table 3 Parameter estimates and scenario comparison

	S0 No integration	S1 No integration		S2 Bias erosion		S3 Full homogenization	
	literature value	est.	s.e.	est.	s.e.	est.	s.e.
θ^D	3	1.38	(0.16)	0.84	(0.15)	1.56	(0.18)
θ^M	6	1.48	(0.14)	1.45	(0.13)	1.46	(0.14)
δ_{2000} / θ^D_{2000}				1.15	(0.05)	1.08	(0.27)
δ_{2005} / θ^D_{2005}				1.20	(0.05)	1.10	(0.23)
δ_{2010} / θ^D_{2010}				1.22	(0.05)	1.51	(0.25)
δ_{2015} / θ^D_{2015}				1.37	(0.05)	1.20	(0.21)
WMSE	1.351	0.577		0.495		0.567	

Note: Estimated parameter (est.) and standard error (s.e.) are provided for scenario S1 – S3. See **Table 2** for descriptions of scenarios. The year-specific integration parameters, δ_n and θ_n^D, are estimated for S2 and S3, respectively.

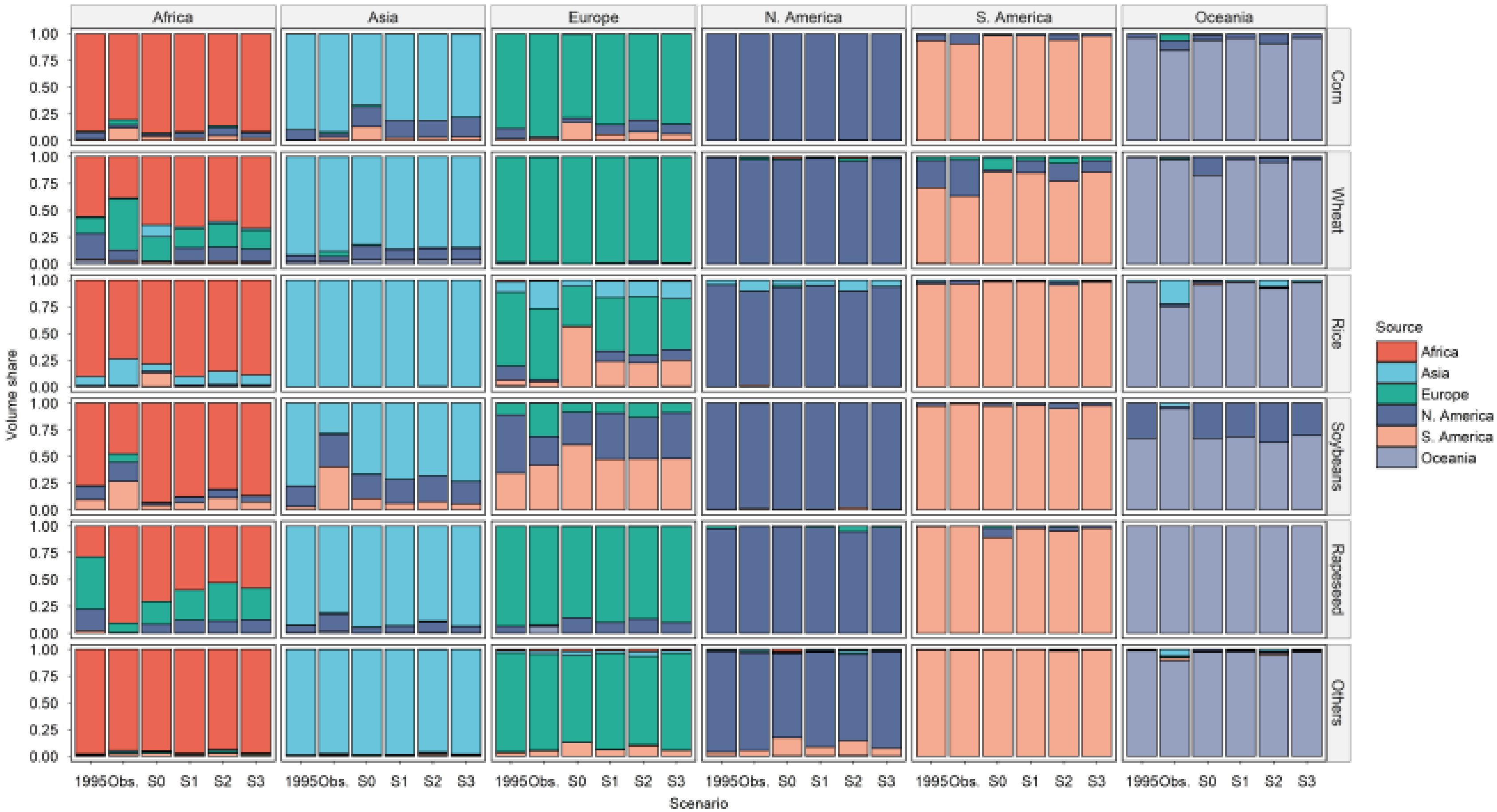

Fig. 4 Comparisons between observed and projected bilateral trade volume shares (across sources) in 2015. Each bar represents the share of consumption volume from a source region over the total consumption in 2015 for a crop (rows) in an importing region (columns) in observations (obs.) or other scenarios. The corresponding volume results are provided in **Fig. S7**.

We estimated standard errors of the estimated parameters based on the Hessian matrix approximated in the nonlinear weighted least squares optimization (Venables and Smith, 2017). The estimated parameters in all scenarios are statistically larger than zero. The optimized parameters in S1, $\theta^D = 1.38$ and $\theta^M = 1.48$, while statistically significant, are much smaller than the widely used literature values applied in S0. The literature parameter of $\theta^M = 6$ was an average estimate in Hertel et al. (2007) for crops based on cross-sectional variations in trade cost, and $\theta^D = 3$ was interpolated based on "rule of two". In general, trade elasticity tends to be smaller when regions are more aggregated, or time-series factors are considered (Ahmad et al., 2020; Bajzik et al., 2020). When the model captured the trend of home bias erosion in S2, the trade parameters became even smaller ($\theta^D = 0.84$ and $\theta^M = 1.45$). Note that if using θ^D and θ^M estimated in S2 but fix preference parameters ($\delta_n = 1$), the WMSE would increase to 0.586. That is, echoing Hillberry et al. (2005), the missing of market integration implied by preference bias erosion could be partly compensated by using relatively larger Armington trade parameters. However, such a remedy is uncertain and compromised given Armington preference shocks' unique role, particularly in long-term modeling. Besides, the estimated θ_n^D across years in S3 were not statistically different. This may also indicate that the dispersion of the preference distribution, which implies the heterogeneity of preference or products did not change significantly in the study periods.

We observed that in our data of bilateral trade, the variations across time were much smaller than variations across crops or regions (see column log(obs.) in the results of the analysis of variance (ANOVA) presented in **Table 4**). It also implies cross-sectional weights could play an important role in the estimates. **Table 4** also shows the relative contribution of variance in the model's error across variables and scenarios. Because of allowing dynamic home preference bias erosions, the root mean squares (RMS) of year in S2 was much smaller than other scenarios. Notably, the share of unexplained time-series variations in bilateral trade (calculated using the sum of squares in **Table S1**) decreased from 12% in S1 to 2% in S2. These results highlighted the critical role of a bias erosion trend in long-term multiregional economic projections. Crop contributed even higher variations in the error of bilateral trade volume than bilateral relationship. It indicates differentiating trade parameters across crops could significantly improve the model. Also, the model generally explains better variations in trade volume than prices (i.e., across crops and bilateral regions). Though S3 performed relatively better in explaining price variations than S2, its overall performance was poorer. Thus, we focus mainly on exploring the bias erosion scenario in the later analysis in this paper.

The model allowing a dynamic trend of home bias erosion tended to explain overall variations better than otherwise. The estimated bilateral trade results from S2 are provided in **Figs. S8 – S9**. The error from the simple model could still be large for certain regions and crops. Compared with WMSE, MAPE is a more communicative measure of model performance. The consumption share weighted MAPE in S2 was about 12% for bilateral trade volumes and 18% for prices, and 15% overall. Though the model showed better performance for volumes than prices at the weighted mean level, volumes can have significantly larger variations, particularly for regions with small trade flows (see **Table S2** for the further decomposition of the weighted MAPE). For reference, if we were to use the base year (1995) values as estimates, the weighted MAPE would be 28% for bilateral trade volumes and 25% for prices, and 27% overall. If using very large Armington parameters (i.e., $\theta^D = \theta^M = 25$ in S0) to mimic elastic trade responses in IWM, the weighted MAPE could be 42% for bilateral trade volumes and 19% for prices, and 30% overall. Echoing previous studies, a well-parameterized Armington model performs significantly better than an IWM (Hertel et al., 2014) or non-model approaches (Dixon and Rimmer, 2010b).

Table 4 Analysis of variance in observed data and errors across scenarios. ANOVA is performed for observation data, log(obs.), and model estimated errors, log(obs. / est.), across three factors including crop, year, and bilateral relationship. All scenarios have the same degrees of freedom (Df). The root mean squares (RMS), calculated as the square root of Df weighted sum of squares, are presented. The same weights used in parameter estimates are applied. The corresponding sum of squares are provided in **Table S1**.

Variable	Source of variation	Df	log(obs.)	log(obs. / est.)			
				S0	S1	S2	S3
			RMS	RMS	RMS	RMS	RMS
Bilateral trade	Crop	5	2828***	434***	517***	562***	533***
	Year	3	446**	127	154	60	155
	Bilateral regions	35	2180***	569***	377***	301***	356***
	Residuals	759	196	197	117	113	118
Prices	Crop	5	521***	337***	341***	353***	345***
	Year	3	726***	26	46	37	47
	Bilateral regions	35	270***	65***	66***	87***	79***
	Residuals	759	59	41	40	40	41

The single asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance levels of 5%, 1%, and 0.1%, respectively, from the F test.

4.2. Bias erosion sensitivity tests

In the bias erosion scenario presented in **Table 3**, the implied integration rate (δ_n) across periods were nonlinear and uncertain. The $\delta_{2015} = 1.37$ implies an annual integration rate of about 1.016 or a half-life of 44 years. In other words, the results indicate that it takes about 44 years to reach half of the global agricultural market integration effect from a full home preference bias erosion. The range of the home bias erosion half-life at a 95% confidence level is 37 – 57 years. Furthermore, the integration rate in 2010 relative to 2005, $\frac{\delta_{2010}}{\delta_{2005}} = 1.01$, was smaller than the rate estimated in other periods. This was likely because the segmentations driven by world food crises around 2008 and 2011 were reflected in the data and captured by the model. As a result, the rate of bias erosion in the period became relatively slower. Here, in the context of the bias erosion scenario, we test the sensitivity of the hindcast optimizations to several key model parameters and assumptions, including crop demand and land supply elasticities, cross-sectional weights ($W_{m,n}$) in WMSE, and the base year.

By default, the model used 1 for the CES crop demand parameter and -1 for the land supply logit exponent. Instead of determining the two parameters in the hindcast optimization, we fixed them to provide consistent comparisons across scenarios. But we test boundary values of [0.25, 2] for the CES parameter and [-0.75, -1.5] for the land supply logit parameter. The results, presented in **Table 5**, demonstrated that the estimated parameters, particularly for the bias erosion parameters, are reasonably robust in these tests. Since WMSE measures goodness-of-fit in relative terms, bilateral flows with small volumes tend to have more considerable variations or more pronounced trade responses. In contrast, large flows tend to be relatively more stable. The cross-sectional weights in WMSE play a key role in considering the heterogeneity. The model, by default, used the square root of trade volume as the weight. We also test an alternative weight of logarithmically scaled trade volume ($W_{m,n} = \ln(1 + Q_{m,n})$; **Fig. S7**) to place relatively higher weights on small flows. The results (last column in **Table 5**) showed a higher regional Armington parameter (θ^D) and larger WMSE. However, the implied magnitude and trend of home bias erosion ($\delta_{2015} = 1.38$) were comparable to results from using the default weights. Note that the bias erosion scenario (S2) still performed better than other integration scenarios with the alternative weight (see **Table S3**).

Table 5 Sensitivity analysis of the bias erosion scenario around demand and supply parameters and WMSE weights

	CES demand (0.25)		CES demand (2)		Logit land supply (-0.75)		Logit land supply (-1.5)		Weight ($W_{m,n}$) $\ln(1+Q_{m,n})$	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
θ^D	0.83	(0.14)	0.79	(0.14)	0.89	(0.15)	0.79	(0.15)	1.38	(0.17)
θ^M	1.44	(0.13)	1.43	(0.14)	1.45	(0.14)	1.43	(0.13)	1.12	(0.15)
δ_{2000}	1.15	(0.05)	1.15	(0.05)	1.15	(0.05)	1.15	(0.05)	1.19	(0.06)
δ_{2005}	1.20	(0.05)	1.20	(0.05)	1.20	(0.05)	1.20	(0.05)	1.29	(0.06)
δ_{2010}	1.22	(0.05)	1.21	(0.05)	1.21	(0.05)	1.22	(0.05)	1.24	(0.06)
δ_{2015}	1.37	(0.06)	1.37	(0.05)	1.36	(0.05)	1.38	(0.05)	1.40	(0.07)
WMSE	0.498		0.504		0.497		0.492		1.625	

The base data in an economic equilibrium model could affect the calibration of the behavior parameters so that either hindcast or projections could be sensitive to the base year. **Table 6** compares parameter estimates across different base years in the bias erosion scenario. The estimated parameters are all statistically significant. θ^D ranged from 0.35 (2005 base year) to 0.84 (1995 base year) and θ^M ranged from 0.93 (2010 base year) to 1.45 (2005 base year). These Armington parameter ranges are generally comparable to literature estimates considering time-series factors (Ahmad et al., 2020; Hillberry and Hummels, 2013). The integration rate (δ_n) is one in a base year and the estimated δ_n can be compared across years. With a base year of 2010 or 2015, the segmentation in the food crisis period (2010) was underlined as δ_{2010} was the smallest across periods. Regardless, results from all base years except 2015 captured a significant global agricultural market integration implied by home bias erosion over the whole study period ($\frac{\delta_{2015}}{\delta_{1995}} > 1$). Notably, the estimated $\frac{\delta_{2015}}{\delta_{1995}}$ decreased when more recent base year was used. It reveals an essential difference between hindcast (forward projection) and backcast (backward projection) that the information was asymmetric. That is, behavior parameters calibrated to a backcast base year (e.g., 2015) may have partly captured the market integration effects. Thus, compared with hindcast, backcast estimated a slower trend of historical market integration implied by home bias erosion. Furthermore, the WMSE is the smallest with the 2005 base year, mainly because the projection time "distance" is the smallest. In other words, the model is more accurate at projecting more recent years. It explains why the WMSE under the base year of 1995 and 2015 are relatively larger.

Table 6 Sensitivity of parameter estimates to base year in the bias erosion scenario

	Base year 1995		Base year 2000		Base year 2005		Base year 2010		Base year 2015	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
θ^D	0.84	(0.15)	0.78	(0.11)	0.35	(0.11)	0.68	(0.13)	0.72	(0.13)
θ^M	1.45	(0.13)	0.90	(0.10)	0.93	(0.12)	0.85	(0.13)	1.08	(0.14)
δ_{1995}	1	-	0.98	(0.03)	0.99	(0.03)	1.07	(0.03)	1.01	(0.03)
δ_{2000}	1.15	(0.05)	1	-	1.00	(0.02)	1.10	(0.03)	1.02	(0.03)
δ_{2005}	1.20	(0.05)	1.04	(0.03)	1	-	1.07	(0.03)	1.01	(0.03)
δ_{2010}	1.22	(0.05)	1.05	(0.03)	1.02	(0.02)	1	-	0.95	(0.02)
δ_{2015}	1.37	(0.05)	1.17	(0.03)	1.14	(0.02)	1.13	(0.03)	1	-
WMSE	0.495		0.251		0.213		0.232		0.274	
$\frac{\delta_{2015}}{\delta_{1995}}$	1.37		1.20		1.15		1.06		0.99	

5. Discussion and implications

In the context of an Armington model, we demonstrated the law of one "preference" (preference bias erosion) permits considering all aspects of market integration that are not explicitly modeled. That is, Armington preference bias erosion offers a practical and promising approach to capture the trend of market integration beyond tariffs and transport costs reduction. In this section, we test home bias erosion scenarios in long-term agroeconomic projections using GCAM and discuss the trade and land use implications (**Section 5.1**). Issues on the extensive trade margin and other limitations are also discussed (**Sections 5.2** and **5.3**).

5.1. Implications of bias erosion in long-term projections

The long-term assessments of global economics and related climate or environmental implications are highly sensitive to the magnitude of global market integration. Future international trade and globalization scenarios are key components in developing Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2017). When translating the qualitative descriptions of future trade scenarios to quantitative modeling, existing studies focused mainly on reducing tariffs and transport costs (Dellink et al., 2017; Fujimori et al., 2017). However, reduction in tariffs and transport margin may only explain a fraction of global market integration, as there are many other drivers, such as revolutions of information and communication technologies and reductions in NTB (e.g., regulatory commitments in preferential trade agreements such as labeling rules, administered projection, processing time)[5] (Anderson, 2010; Balistreri and Tarr, 2020).

GCAM is a well-established model and has been widely used in evaluating long-term socioeconomic and alternative scenarios (Calvin et al., 2017a; Graham et al., 2020). The model uses assumed socioeconomic drivers in SSP2 in the reference scenario and runs to 2100 with 5-years steps (see Calvin et al. (2019) for a detailed description of GCAM and its reference runs). The model has a detailed representation of agricultural production and land use in 32 regions. The logit-based Armington approach was recently incorporated into the model (Snyder et al., 2020; Zhao et al., 2021). By default, the Armington preference parameters are calibrated to the data in the base year of 2015 and fixed in projections. Note that GCAM and the associated data system are publicly available (Bond-Lamberty et al., 2019; Calvin et al., 2020). Additional information on GCAM is provided in **SI**.

[5] For example, the ad valorem equivalents (AVE) of NTB was estimated to be about 15.8% between the US and EU for primary agricultural products, significantly higher than the 2-3% average tariffs between the two regions (Egger et al., 2015).

We test two global agricultural market integration scenarios to allow home bias erosion for crops in GCAM following the historical trend estimated in this paper. The first scenario, default home bias erosion, uses the average integration rate ($\frac{\delta_n}{\delta_{n-5}} = 1.08$) in the default scenario and implies a half-life of 45 years. The second scenario, high home bias erosion, uses the integration rate ($\frac{\delta_n}{\delta_{n-5}} = 1.23$) from the highest upper value in the 95% confidence intervals across study periods. It implies a half-life of about 17 years.

The trade impacts of home bias erosion scenarios are presented in **Fig. 5**. With the trend of bias erosion, crop consumers will gain more balanced accessibility to both domestic and international markets. Thus, crop trade generally expands, and the pattern of global production and consumption adjusts. The total net trade for the four major crops (coarse grains, oil crops, wheat, and rice) increased by 425 million tons (Mt) in the default integration scenario and by about 600 Mt in the high scenario. Regions with relatively stronger home bias under the GCAM reference scenario, e.g., African regions, China, Southeast Asia, and India, would source more products from international markets. Notably, such integration facilitated shifts of agricultural production to more productive regions, e.g., the USA and Brazil. As a result, the world average yield increased by about 3% in the default scenario and 4.3% in the high scenario (on average for major crops). Driven by the higher crop yields, about 27 (default) – 47 (high) million ha (Mha) of cropland at the world level could be saved (**Fig. 6**). The cropland decrease was about 2.2% – 3.9% of the 1200 Mha total cropland projection in the GCAM reference scenario. However, there could be relatively larger regional land use implications, and the impact of the integration could play more critical roles in evaluating alternative scenarios of changing environment and climate.

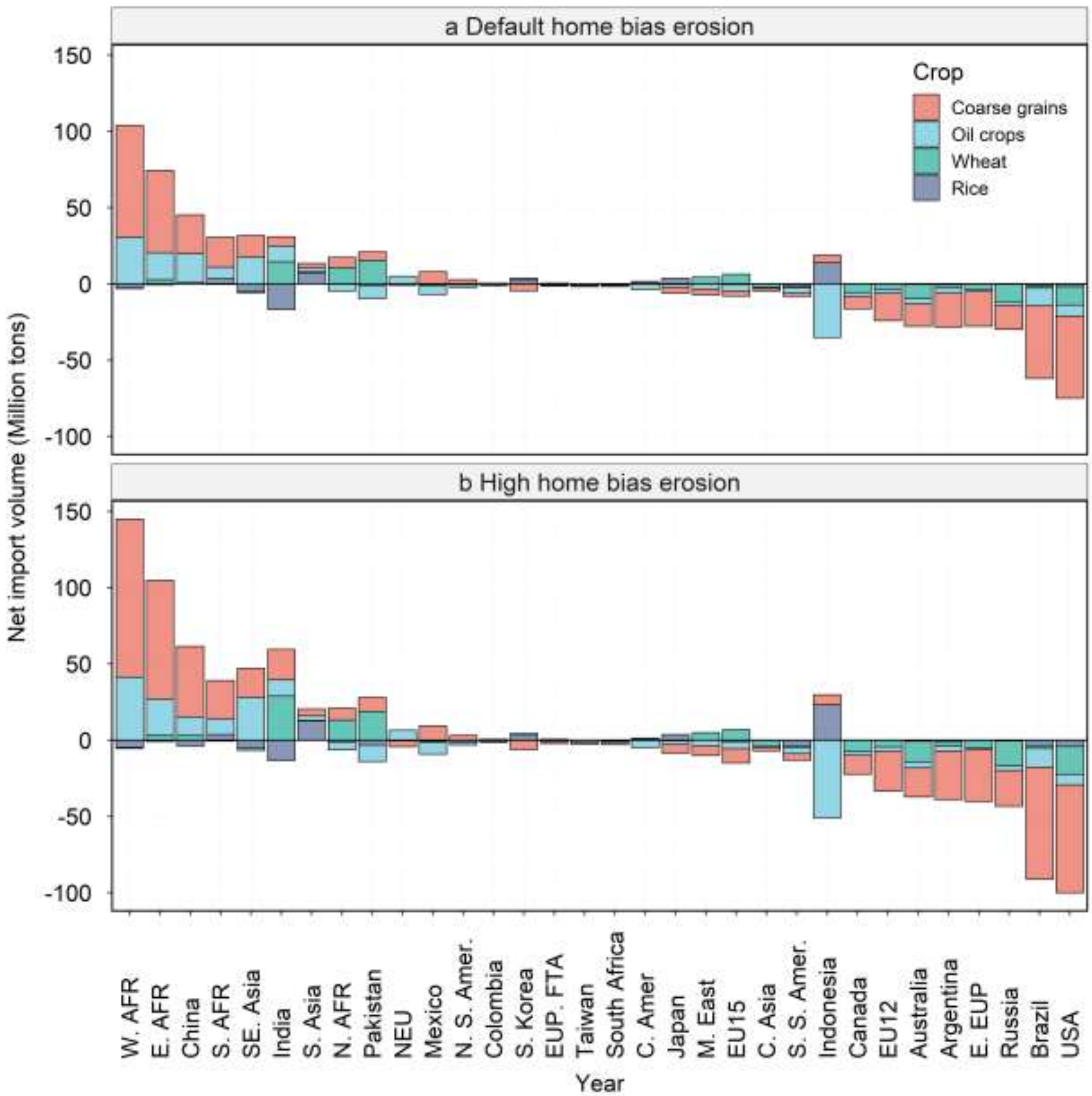

Fig. 5 Market integration impacts on regional net trade of major crops by the end of century. Bars represent changes in net trade (import) relative to the GCAM reference projection in 2100 for major crops (distinguished by color) in GCAM region from two market integration scenarios: default home bias erosion (**a**) and high home bias erosion (**b**). Data source: GCAM simulations

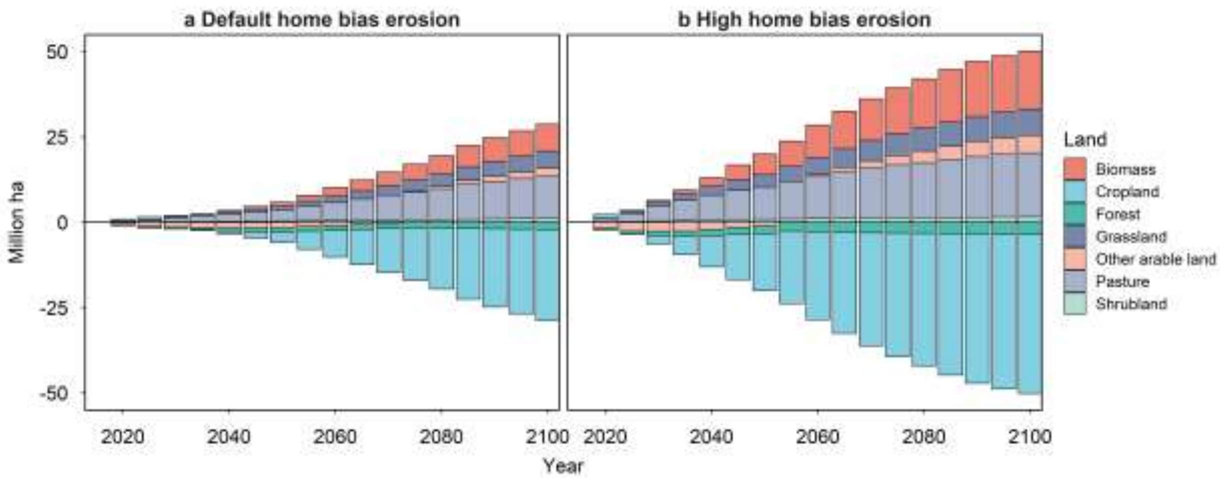

Fig. 6 Market integration impacts on global land use change by the end of century. Bars represent changes in areas of land (distinguished by color) relative to the GCAM reference projection in 2100 from two market integration scenarios: default home bias erosion (**a**) and high home bias erosion (**b**). Data source: GCAM simulations

5.2. Extensive trade margin

A critical issue of the Armington approach or gravity models on the extensive margin is that trade partnerships are locked at the initial state. The model cannot project new partnerships if two regions do not trade in the base year. This issue affected the highly aggregated model used in this paper to a minimal extent. Few regions with zero bilateral trade flow in 1995 generated positive trade flows in later years (e.g., rapeseed export from Asia to Africa; **Table S4**), but the new trade flows were small so that their impacts on the hindcast optimization could be ignored. Nevertheless, this extensive margin issue could be amplified in long-term projections using models with more disaggregated sectors and regions. When a bilateral trade flow is zero in the base data, the Armington preference parameter (T_i) is also calibrated to zero. In the conventional assumption or the bias erosion scenario proposed in **Section 2.2**, the preference parameter will remain zero. However, it is possible to extend the bias erosion scenario to trigger new trade relationships, requiring further investigations though. Note that such technique of introducing new technologies during simulations through modifying preference parameter (logit share-weights), has been applied in GCAM. For example, dedicated biomass production was introduced into GCAM in a future year by increasing the preference share in the logit land supply (Kyle et al., 2011; Wise et al., 2014).

5.3. Limitations and future studies

The theoretical model developed in this study is relatively simple, with highly aggregated regions and crops. The trade across the six aggregated regions (continents) accounted for about 66% in 1995 (67% in 2015) of the global trade volume of major crops (i.e., corn, soybeans, wheat, and rice). That is, over 30% of interregional crop trade was treated as domestic trade. Also, we did not estimate crop-specific trade parameters or region-specific market integration parameters because of the limited coverage of crops and periods and concerns of computation and overfitting. In addition, our study focused on home bias erosion in the domestic – foreign nest of the Armington structure. There could also be preference changes in the foreign – foreign nest, though likely to a smaller magnitude than home bias erosion. Futures studies permitting region- and crop-specific parameters and international bias erosion using improved data could significantly enhance the modeling and hindcast performance.

While simple, our model can be easily extended, and the hindcast optimization framework can be broadly applied beyond examining global market integration in agricultural sectors. Under the Agricultural Model Intercomparison and Improvement Project (AgMIP), several widely used global economic models were compared for their 2050 agroeconomic projections (Nelson et al., 2014b; von Lampe et al., 2014). Future model comparisons with harmonized hindcast experiments could provide additional insights. Notably, model validation is not a once and for all task given the continuing data update and model development (Schwanitz, 2013).

6. Conclusions

In this paper, we develop a framework for validating a multiregional agricultural trade equilibrium model using hindcast experiments with a focus on exploring the trend and impact of global agricultural market integration. Particularly, we demonstrate a theoretical reconciliation between the Armington approach and a fully integrated world market approach by stipulating a dynamic trend of Armington preference bias erosion and product homogenization. Following the theoretical intuition, we generalize the Armington approach by permitting home preference bias erosion to portray a dynamic trend of market integration.

We build a simple agricultural economic equilibrium model and conduct hindcast experiments to examine the historical trend of market integration. The results from our hindcast experiments indicated that there was a significant global market integration trend implied by historical home bias erosion (a half-life of 44 years). That is, the conventional assumption of fixed Armington preference bias could lead to the “missing globalization” problem and underestimate gains from market integration. Allowing the dynamic trend of market integration implied by bias erosion also showed important implications for estimating trade elasticities and long-term agroeconomic projections. By testing the future market integration trend implied by historical home bias integration in GCAM, we show a high sensitivity of long-term agroeconomic projections to future trade and market integration scenarios. The results suggested that preference bias erosion, as an aggregate representation of market integration drivers besides tariff and transportation cost reductions, provides a promising and practical way to consider a broader aspect of global market integration in evaluating long-term socioeconomic scenarios.

Model and code availability

We build an R package (tradecast) for the model developed in this study. A repository including the data, model, and R code for generating main figures will be made available when published. Also, the GCAM model is publicly available (github.com/JGCRI/gcam-core).

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