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Micro-Macro Impacts of Climate-Change on Agriculture and Food Markets

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This paper develops a structural econometric model of farmland allocation that is linked to a market-level demand model. The farmland allocation model accounts for the presence of corner solutions in land-share decisions, which enables using disaggregated data for the estimation, and thereby allows treating prices as exogenous. Under partial equilibrium in the markets of vegetative products, the integrated model is then used to simulate the impacts of climate change on production, prices, agricultural profits and consumer surplus, making explicit the production responses of the micro units used for estimating the land-use model. We apply the method to Israeli data, and obtain negative projections of farm profits and consumer's surplus driven by climate change. Importantly, the effects of climate change on farm profits are significantly smaller compared with the case in which the price-feedback effects on agricultural supply are not accounted for.

1. Introduction

Economic assessments of climate-change impacts on agriculture that ignore price responses to changes in supply could lead to biased results. Owing to their ability to capture economic interactions among quantities and prices of multiple products and regions, general and partial equilibrium models are powerful tools for assessing climate change effects on agriculture. This paper attempts to fill a methodological and empirical void by combining a structural econometric micro-level model of farmland allocation with a macro-level market model. This empirical framework is capable of exploiting disaggregated data of farmers' production decisions and its sample heterogeneity and therefore avoids the aggregation bias of partial and general equilibrium models that rely on the supply behavior of representative agents only.

When used, macro-level models are frequently linked with micro-level agricultural production models that represent farmers' optimal responses to changes in exogenous variables such as climate, prices and policy instruments. So far, such micro-level models were developed based on the mathematical programming approach, in which agricultural production is represented explicitly, and therefore these models can be easily integrated with macro-level equilibrium models (e.g., Howitt et al., 2003; Arndt et al., 2011; Arndt et al., 2012; Palatnik et al., 2011; Robinson et al., 2012). The agricultural production functions in the micro-level models are often calibrated, or derived from estimates external to the model, and therefore they reflect the behavior of representative agents (Michetti, 2012). That is, there is no direct linkage between the macro-level equilibrium model and the dataset used to derive the agricultural production functions in the micro-level model. Consequently, the overall analysis does not capture the sample heterogeneity present in the data with regard to farmers' productivity and production decisions that are sensitive to changes in exogenous and endogenous variables. Moreover, while programming models are based on theoretical economic assumptions (e.g. profit function specifications), they cannot test for the validity of these assumptions. The empirical framework built in this paper can directly address those various concerns.

Two types of econometric-based models are widely used in economic analyses of climate change, both are based on the idea that observed farm management practices and profits reflect farmers' optimal responses to external factors. The first are land-use models, which utilize spatial variability in climate conditions to explore climate-change adaptation measures (e.g., Mendelsohn and Dinar, 2003; Kurukulasuriya and Mendelsohn, 2008; Seo and

Mendelsohn, 2008; Fleischer, Mendelsohn, and Dinar, 2011). The second type of models employ the *Ricardian* or *Hedonic* approach (Mendelsohn et al., 1994; Schlenker et al., 2005; Deschênes and Greenstone, 2007), in which spatial variation in farm profits or land values are explained by economic and environmental variables, including climate. However, both types of models do not explicitly estimate production functions, and therefore cannot be linked to macro-level models; hence, prices are considered exogenous and fixed when the consequences of future climate changes are simulated (Cline, 1996; Darwin, 1999).

In this paper we adopt the structural modeling approach used by Kaminski, Kan and Fleischer (2013). The approach relies on a recursive decision-making process: farmers allocate land across crop bundles at the beginning of the growing season based on anticipated end-of-season per-hectare profits of these bundles, where these anticipated profits are based on farmers' long-term experience with respect to weather during the growing season; that is, based on climate. Hence, spatial variation in climate conditions is reflected by spatial variation in the anticipated relative profitability of bundles, which in turn dictates the observed spatial variation in land allocation among bundles. The profit function assumed by Kaminski, Kan and Fleischer (2013) enables the use of readily available crop-acreage data for estimating per-hectare production and cost functions, as well as testing whether the estimated profit function complies with economic theory. The use of land-use data rather than land values avoids the need to rely on the presence of perfect input and land markets, as assumed by the Ricardian approach. More important for the purpose of this study, agricultural production and output prices are expressed explicitly in this model and enter the land use function that is empirically estimated; this key property is exploited to link this structural econometric micro-level model of agricultural supply with a macro-level demand model, such that the two models feed into one another to determine the equilibrium quantities and prices of agricultural products.

Our analysis has two major advantages over the modeling strategy used by Kaminski, Kan and Fleischer (2013). First, by using regional land-allocation data, they avoided the need to deal with corner solutions (land shares of 0 or 1). However, at the regional level, prices may be endogenous. Our analysis uses disaggregated data at the community level, where prices can be safely considered exogenous. This requires us to use an estimation strategy that controls for the presence of non-negligible number of observations with corner solutions. Second, Kaminski, Kan and Fleischer (2013) simulated the impact of climate change while ignoring the responses of output prices to supply changes. We account for these price feedback effects by linking the micro-level land-use model to a macro-level demand model, and simulate country-wide partial equilibrium. Therefore, prices are exogenous in the estimation of micro-level production decisions and agricultural supply, but become endogenous in the simulations under partial-equilibrium conditions.

We illustrate the performance of our approach using Israeli data. Israel is particularly suitable for studying the impact of climate change on agriculture, because of its diversified climate conditions, from subtropical in the north to arid in the south, within a relatively small distance. In addition, Israeli agriculture is technologically advanced, and has enjoyed decades of experience of adaptation to varying and unfavorable climate conditions. Not surprisingly, previous studies of the impact of climate change on Israeli agriculture cover the entire range of methodologies described above. Specifically, Kan et al. (2007) applied the mathematical programming technique to regional data from Israel, while Fleischer et al. (2008) applied the Ricardian approach to micro data. The impact of climate change on agricultural decisions in Israel was analyzed further by Fleischer et al. (2011), who used a discrete choice model in which farmers choose among a set of crop-technology bundles, and by Kaminski, Kan and Fleischer (2013) based on their aforementioned structural model. In all of these studies, output prices were assumed constant and exogenous in the simulations of climate change. This assumption is particularly problematic in the case of Israel, and could lead to considerable bias even if global food prices are stable; this is because the Israeli government limits imports of many agricultural products through import tariffs, quantity limitations, and other institutional means (OECD, 2010); hence, many crop prices are determined internally.

Therefore, a partial equilibrium model, in which prices are determined endogenously, is much more suitable for assessing the ramifications of climate change effects in the case of Israel. Furthermore, this also opens up a public economic perspective of the distribution of climate change effects between producers and consumers (since the latter are now affected by climate-driven price changes), with both efficiency and equity concerns as to which public policies could better mitigate potentially-harmful climate-related impacts onto economic activities.

We use existing projections of climate change for a number of key climate variables that are relevant for agricultural production over the next few decades (Krichak et al., 2011) in order to simulate changes in crop portfolios, farmland allocations, agricultural production, output prices and producer and consumer surpluses. We compare the results obtained under two policy scenarios: (1) free trade, where the prices of all crop outputs equal their world counterparts, which are assumed fixed; simulations under this scenario are equivalent to results of a model that does not allow the feedback effect of prices on land-allocation decisions and agricultural supply, as in earlier econometric-based studies; (2) a scenario of restricted trade, where local prices are determined by partial equilibrium conditions in the presence of import tariffs. Our simulations predict substantial reduction in producer and consumer surpluses, with those welfare losses being of significant lower absolute value under the restricted-trade scenario.

In the next two sections we describe the micro-level supply model and the link between the micro- and macro-levels, respectively. After that we present the data sources. Then we move to the empirical results, first to the estimation of the land-use model and then to the simulations of climate change impacts on profits and consumer surplus. The final section summarizes and discuses implications of the results and their policy relevance.

2. Micro-Level Supply Model

We model a vegetative agricultural sector in a small open economy where all goods are freely traded except for a subgroup of agricultural products, which are subject to import tariffs. Consider *J* potential bundles of crops (i.e., groups of field crops, vegetables, etc.) to be grown in a farm, and let s_j be the land share of crop bundle *j*, $j = 1,...,J$. The objective of the farmer is to choose the vector of land shares, **s**, so as to solve the problem:

$$\max_{\mathbf{s}} \Pi = \sum_{j=1}^{J} s_j \left(\rho_j y_j - c_j \right) - c(\mathbf{s}) \tag{1}$$

$$\text{s.t.} \quad \sum_{j=1}^{J} s_j = 1 \text{ and } s_j \geq 0 \quad \forall \ j = 1,..., J$$

where Π is the farm's profit (normalized to one hectare), ρ_j is the bundle's expected output price index, y_j is the expected end-of-season per-hectare yield of bundle *j*, c_j stands for the expected end-of-season bundle-specific per-hectare explicit costs, and $c(\mathbf{s})$ is the implicit production and management cost function, which represents costs that are neither bundle specific, nor independent across bundles; for example, $c(\mathbf{s})$ incorporates the costs associated with unfeasible production of certain crop bundles in rotating systems and the allocation of quasi-fixed inputs such as labor and machinery across crop bundles with different patterns and cultivation timing. The function $c(\mathbf{s})$ captures the constraints on farmers' acreage decisions as motives for bundle diversification; it embeds the shadow values of all binding constraints on acreage allocation choices (except the total land constraint) and represents the non-linear effects of the allocative input **s** on farm profits, a feature which is pivotal in positive mathematical programming (Howitt, 1995).

We further specify the yield of each bundle *j* by the linear function $y_j = \mathbf{b}_j\mathbf{x}$, where $\mathbf{b}_j$ is a vector of coefficients, and $\mathbf{x}$ is a set of exogenous variables, including climate variables and farm characteristics.[1] The bundle-specific explicit costs are specified by $c_j = \gamma_j w + \delta_j$, where *w* is the price index of purchased production inputs and γ_j and δ_j are coefficients. Thus, the expected explicit per-hectare profit of bundle *j* is:

$$y_j\rho_j - c_j = \mathbf{b}_j\mathbf{x}\rho_j - \gamma_j w - \delta_j \equiv \mathbf{v}_j\mathbf{z}_j \tag{2}$$

where $\mathbf{v}_j = \left(\mathbf{b}_j, -\gamma_j, -\delta_j\right)$ and $\mathbf{z}'_j = \left(\mathbf{x}\rho_j, w, 1\right)$. Noteworthy, the vector of exogenous variables $\mathbf{z}_j$ being bundle-specific due to the multiplication of the variables in $\mathbf{x}$ by the respective output price index ρ_j is crucial for the identification of the production-function coefficients, which in turn allows the link between the micro- and macro-level models.

The function $c(\mathbf{s})$ plays a key role in the econometric analysis, as its functional specification determines the attributes of the structural equations to be estimated, and therefore the required estimation procedure. Carpentier and Letort (2013) and Kaminski, Kan and Fleischer (2013) assumed the opposite-entropy function:

$$c(\mathbf{s}) = \frac{1}{a}\sum_{j=1}^{J} s_j \ln\left(s_j\right) \tag{3}$$

where the *a* parameter, measured in land per money unit and therefore assumed positive, reflects the “weight” of the implicit production and management costs in the profit function. This is a negative, non-monotonic convex function with respect to s_j, $j = 1,...,J$. The non-monotonicity implies that, ceteris paribus, the implicit costs decline with s_j for $\exp(-1) \geq s_j \geq 0$ and increase with s_j when $1 \geq s_j > \exp(-1)$. Since land shares are negatively correlated among them through the land constraint, $c(\mathbf{s})$ has a minimum at $s_j = 1/J$ for all $j = 1,...,J$.

The opposite-entropy specification leads to the multinomial logit functional form for the optimal land shares:

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[1] While the linear function is adopted to facilitate the analysis, the model can be easily extended; for example, Kaminski, Kan and Fleischer (2013) specified y_j as a quadratic function of per-hectare bundle-specific endogenous inputs with structural parameters, and thereby accounted for the impact of climate change through optimal input applications and identified the effect of climate variables on attributes of agricultural production technologies.

$$s_j^* = \frac{\exp\left(a\mathbf{v}_j\mathbf{z}_j\right)}{\sum_{j=1}^{J}\exp\left(a\mathbf{v}_j\mathbf{z}_j\right)} \tag{4}$$

where s_j^* is the optimal land share of bundle *j*.

Let *i* denote a farm in a sample of *I* farms. To enable estimation we specify bundle *J* as the reference bundle. The selection of the reference bundle is not just a technical issue, since, as will be shown later, in order to simulate partial equilibrium, one should identify the parameters of the linear yield function $\mathbf{b}_j$ for all the *J* bundles. We take advantage of the fact that farmers typically devote non-cultivated agricultural land to roads, storage lots and other uses that support the production in the cultivated areas. As in crop cost-and-return studies (e.g., see studies by UCDAVIS), the revenue contribution of these supportive lands is reflected only through the cultivated areas; that is, $\mathbf{b}_J = 0$. Eq. (4) can now be used to obtain a system of $J-1$ linear land-share regression equations:

$$\ln\left(s_{ji}^*/s_{Ji}^*\right) = \mathbf{V}_j\mathbf{z}_{ji} + u_{ji} \tag{5}$$

where u_{ji} is an error term and $\mathbf{V}_j = \left(a\mathbf{b}_j, -a\left(\gamma_j - \gamma_J\right), -a\left(\delta_j - \delta_J\right)\right) \equiv \left(\mathbf{B}_j, G_j, D_j\right)$; this implies that we cannot identify a and $\mathbf{v}_j$, but only the coefficients $\mathbf{B}_j$, G_j and D_j in $\mathbf{V}_j$.

Being flexible, conveniently estimable due to linearity, ensuring that for each observation the predicted land shares are between 0 and 1 and add up to 1, the multinomial logit functional form was favored over alternative specifications in land-use analyses (e.g., Hardie and Parks, 1997; Miller and Plantinga, 1999). However, Eq. (5) cannot treat corner solutions. This limitation may not emerge when estimation is based on regionally aggregated data, where zero land share observations are seldom (e.g., Wu and Segerson, 1995); but at the regional level prices may be endogenous. We therefore use disaggregated data to discard the endogeneity of prices,[2] but this may involve a non-negligible number of observations with corner solutions. Hence, instead of estimating Eq. (5), we estimate Eq. (4) using the quasi maximum likelihood approach, by maximizing the fractional multinomial logit likelihood function (Papke and Wooldridge, 1996; Buis, 2010):

$$\ln\left(L\right) = \sum_{i=1}^{I}\sum_{j=1}^{J} s_{ji}\ln\left(s_{ji}^*\right) \tag{6}$$

[2] Alternatively, one may employ simultaneous estimation of both prices and land shares; however, this poses two challenges: (i) an identification strategy and the availability of instrumental variables for regional prices in the micro-level estimations of the econometric model, (ii) a tractable partial or general-equilibrium model with simultaneous and endogenous price determination adjusting with the outputs of the micro-level estimations.

where s_{ji} is the observed land share, and s_{ji}^{*} is as specified in Eq. (4). To enable estimation we divide and multiply s_{ji}^{*} in Eq. (4) by $\exp\left(a\mathbf{v}_J z_J\right)$, obtaining

$$s_{ij}^{*} = \exp\left(\mathbf{V}_j \mathbf{z}_{ji}\right)\left(\sum_{j=1}^{J} \exp\left(\mathbf{V}_j \mathbf{z}_{ji}\right)\right)^{-1}.$$

While this land-use model is structural in the sense that it links the per-hectare profit functions expressed in the farming optimization problem to optimal land-use decision, not all the profit-function parameters are identifiable, among them is the *a* parameter. Kaminski, Kan and Fleischer (2013) show that, to enable identification of the parameters $\mathbf{v}_j$ for $j = 1,..., J-1$, *a* can be calibrated by the use of panel data and additional information on crop profitability. As will be shown later, for the purpose of this study—the simulation of partial equilibria—identification of *a* is not necessary, since *a* is canceled out in the equations used for linking the micro and macro models.

3. Linking Micro-Level and Macro-Level Models

Our objective is to link the estimated micro-level supply model with a macro-level demand model for simulating climate-change under partial equilibrium, where this link incorporates the aggregated impacts of climate variables and prices on all the observations in the dataset used for estimating the supply model. We commence with describing the supply side.

Let ϕ_{jt}^{p} denote the simulated output-price index of crop bundle *j* at some year *t*, relative to year 1 (the base year, representing the sample period), so that ϕ_{j1}^{p} is normalized to 1. We define a vector of price indices $\boldsymbol{\phi}_t^p = \left(\phi_{1t}^p,...,\phi_{J-1t}^p\right)$, and the corresponding set of explanatory variables $\mathbf{z}_{ijt}^{'} = \left(\phi_{jt}^p \mathbf{x}_{it}, w, 1\right)$ for every farm $i = 1,..., I$, bundle $j = 1,..., J-1$, and year *t*, where $\mathbf{x}_{it}$ incorporates farm-*i*'s predicted climate variables at year *t*. Accordingly, $\hat{s}_j\left(\mathbf{z}_{it}\right)$ is the predicted land share calculated by Eq. (4) given the set of variables $\mathbf{z}_{it} = \left(\mathbf{z}_{ijt},...,\mathbf{z}_{iJ-1t}\right)$ and the estimated coefficients $\hat{\mathbf{B}}_j$, $\hat{G}_j$ and $\hat{D}_j$. Then, the sample aggregated optimal output value for each bundle *j* is predicted by:

$$\hat{A}_j\left(\mathbf{z}_t\right) = \sum_{i=1}^{I} l_i \hat{s}_j\left(\mathbf{z}_{it}\right)\phi_{jt}^p \hat{\mathbf{B}}_j \mathbf{x}_{it} \tag{7}$$

where l_i is the land area of farm *i*, and $\mathbf{z}_t = \left(\mathbf{z}_{1t},...,\mathbf{z}_{It}\right)$.

We use the *Laspeyres* quantity index to derive the change in the output of crop bundle *j* supplied by local producers in response to changes in the prices and the exogenous variables between year 1 and some year *t*. The local-supply quantity index is:

$$\phi_j^y\left(\mathbf{z}_t\right)=\frac{\hat{A}_j\left(\mathbf{z}_t\right)}{\hat{A}_j\left(\mathbf{z}_1\right)} \tag{8}$$

In view of Eqs. (7) and (8), the parameter *a*, which is incorporated in $\hat{\mathbf{B}}_j$ $(=a\mathbf{b}_j)$, vanishes in Eq. (8), and this property enables the simulation without identification of *a*.

We now turn to the demand side. Similar to the supply, we formulate a bundle quantity index as a function of price indices, which is rather based on country-wide information on individual crops within each bundle. In order to simplify notation, and without loss of generality, assume that the number of different crops in each bundle *j*, $j=1,...,J-1$, is identical and equal to *K*. Denote the price of crop *k*, $k=1,\dots,K$, of bundle *j* in year *t* as p_t^{kj}, and the aggregated quantity of this crop demanded by local consumers as Q_t^{kj}. Also assume that the country-wide aggregate demand function is of the form:

$$Q_t^{kj}=h^{kj}\left(p_t^{kj}\right)^{\beta^{kj}} \tag{9}$$

where β^{kj} is a known demand elasticity, and h^{kj} is a calibrated parameter. Assume further that all crops in each crop bundle *j* satisfy the criteria of a composite commodity, i.e., their prices change proportionately. Define the *Laspeyres* demanded-quantity index, ϕ_{jt}^q, which, based on Eq. (9), becomes a function of ϕ_{jt}^p, as:

$$\phi_j^q\left(\phi_{jt}^p\right)=\frac{\sum_{k=1}^{K}p_1^{kj}Q_t^{kj}}{\sum_{k=1}^{K}p_1^{kj}Q_1^{kj}}=\frac{\sum_{k=1}^{K}p_1^{kj}h^{kj}(p_t^{kj})^{\beta^{kj}}}{\sum_{k=1}^{K}p_1^{kj}h^{kj}(p_1^{kj})^{\beta^{kj}}}=\frac{\sum_{k=1}^{K}p_1^{kj}h^{kj}(\phi_{jt}^p p_1^{kj})^{\beta^{kj}}}{\sum_{k=1}^{K}p_1^{kj}h^{kj}(p_1^{kj})^{\beta^{kj}}} \tag{10}$$

We assume partial equilibrium in the base year ($t=1$), such that $\phi_j^q\left(\phi_{j1}^p\right)=\phi_j^y\left(\mathbf{z}_1\right)=1$ for all $j=1,...,J-1$. In future years, $\mathbf{x}_t$ incorporates the modified values of all climate variables in relation to the base year, such that plugging $\mathbf{x}_t$ into the supply-quantity index in Eq. (8) breaches the equilibrium. If international trade is free, prices are assumed to remain unchanged,[3] and the gap between demand $\phi_j^q\left(\phi_{jt}^p\right)$ and supply $\phi_j^y\left(\mathbf{z}_t\right)$ for every $j=1,...,J-1$

[3] According to Kachel (2003), Israel's agriculture is small enough for not affecting world food prices. While the herein methodology can be employed in a world-level CGE model for simulating climate-change impacts on

equals the import or export of bundle-*j*'s outputs. If trade is bounded by import tariffs, the set of local price indices $\boldsymbol{\phi}_t^p$ would change. Let $\overline{\boldsymbol{\phi}}^p = \left(\overline{\phi}_1^p, ..., \overline{\phi}_{J-1}^p\right)$ be the set of import prices, which equals the world prices plus the country's import tariffs. We simulate partial equilibrium by solving

$$\begin{aligned} &\min_{\boldsymbol{\phi}_t^p} \sum_{j=1}^{J-1} \left(\phi_j^q\left(\phi_{jt}^p\right) - \phi_j^y\left(\mathbf{z}_t\right)\right)^2 \\ &s.t.\ \boldsymbol{\phi}_t^p \le \overline{\boldsymbol{\phi}}^p \end{aligned} \tag{11}$$

Eq. (11) links the supply quantity index, which incorporates all the sample data points, to the demand quantity index, which is based on country-wide aggregated data. In addition, having the base-year country's total production value for every bundle $j = 1, ..., J-1$, $\sum_{k=1}^{K} p_1^{kj} Q_1^{kj}$, one can use the simulated values of $\phi_j^y\left(\mathbf{z}_t\right)$ and $\phi_j^q\left(\phi_{jt}^p\right)$ to compute for every year *t* the country's total value of production supplied by local farmers, $\phi_j^y\left(\mathbf{z}_t\right)\sum_{k=1}^{K} p_1^{kj} Q_1^{kj}$, and the country's value of demanded quantity, $\phi_j^q\left(\phi_{jt}^p\right)\sum_{k=1}^{K} p_1^{kj} Q_1^{kj}$. To compute country-wide agricultural profits one needs to subtract the production costs from the value of locally supplied products. Let L^{kj} be the total land devoted in the country to crop *k* in bundle *j*, and L_j the total land allocated to bundle *j*. Let c^{kj} be the per-hectare production costs of crop *k* in bundle *j*; hence $c_j = L_j^{-1}\sum_{k=1}^{K} c^{kj} L^{kj}$ is the country average per-hectare cost of bundle *j*. Then, the simulated production cost of bundle *j* at year *t*, C_{jt}, is computed by

$$C_{jt} = c_j L_j \left[1 + \hat{s}_{jt} - \hat{s}_{j1}\right] \tag{12}$$

where

$$\hat{s}_{jt} = \sum_{i=1}^{I} \frac{l_i}{l} \hat{s}_j\left(\mathbf{z}_{it}\right) \tag{13}$$

in which *l* is the total agricultural land of the farms in the sample.

world prices under equilibrium, our analysis is limited to the case of Israel's local market under partial equilibrium.

4. Data and Variables

Our data set is a panel of 8,173 observations encompassing 743 agricultural communities (about 85% of all agricultural communities in Israel) over the years 1992-2002, provided by the Israeli Ministry of Agriculture and Rural Development (IMARD). Altogether the sample covers 264,000 hectares—more than 60% of the agricultural land acreage in Israel. The land allocated to each crop bundle is reported for the community as a whole, so we must treat each community as if it was a single decision-making unit. This is in fact true for about 40% of the sample communities, which are Kibbutzim, in which all economic activities, including agriculture, are managed collectively. Another 51% of the sample communities are Moshavim (cooperative villages with individual farms). While each Moshav member can make his own land allocation decisions, being a member of a cooperative imposes some constraints on these decisions (Kimhi, 1998). In only 9% of the sample (private communities) agricultural decisions of the different farmers are completely independent of each other.

Our data comprise aggregated land shares of four crop bundles: vegetables, field crops, fruits, and the reference bundle of non-cultivated agricultural areas. In Table 1 we present the number of observations and average land shares (weighted by total community agricultural lands) of the 8 different portfolios of crop bundles. In 5,081 (62%) of the observations all three crop bundles are selected for production; this highlights the need to account for corner solutions in the estimation. As expected, the land share of field crops is the largest with 45%, ahead of fruits (33%), then vegetables (15%), and non-cultivated areas (6.5%); the latter varies across portfolios between 22% in the communities that produce vegetables only, and 1% when production of vegetables is combined with field crops.

Table 2 defines explanatory variables used in the estimation and reports their sample means and standard deviations.

The climate variables were derived from data produced by RegCM3, a high-resolution, 25-kilometer climate simulation model (Krichak et al., 2011) especially designed for the eastern Mediterranean region. The model provides daily data on ground temperature and precipitation, covering the period 1960-2060, of which the years 1960-2005 are used for validation, and the rest are forecasts of the future periods. While the model does not necessarily predict daily weather very accurately, the daily data enable reproducing changes in the moments of the temporal and spatial distributions of the climate variables, which is what matters most for our analysis. Kirchak et al. (2011) reported that the simulation for the period 1960-2005 was successfully validated by actual climate data collected in land-based monitoring stations. Their projections for the years 2006-2060 were computed by assuming carbon emissions as per the IPCC's A1B scenario (IPCC, 2001), which forecasts rapid economic growth and technological progress along with a decrease in worldwide spatial income inequality. The climate variables from the 25-km resolution points of the RegCM3 model were interpolated to the coordinates of each agricultural community in our sample, using the Inverse Distance Weighting (IDW) method. The power 1 IDW specification was chosen due to its superior robustness (Kurtzman and Kadmón, 1999).

The climate variables we use are annual average temperature and cumulative annual precipitation. Following Kaufman and Snell (1997), Schlenker et al. (2005), and Deschênes and Greenstone (2007), the effect of temperature on crops is represented by Degree Days (hereafter DD). DD is the cumulative number of daily Celsius degrees between 8° and 32° over a given number of days. Richie and NeSmith (1991) provide agronomic and physiological justifications for the use of DD rather than absolute temperatures. We consider the climate conditions simulated by Kirchak et al. (2011) for the 20-year period of 1981-2000 as those that have affected agricultural land use during our sample period 1992-2002; that is, as in Kaminski, Kan and Fleischer (2013), climate variables are time invariant in the estimation. In the simulations of later periods we used computed community-specific moving averages of the projected degree days and precipitation, where the value for each year is the average of the preceding 20 years; Figure 1 presents the projected time paths of country-wide average degree days and precipitation.

Based on these trends one can identify two climate-change phases: in the first, during 2000-2030, both temperature and precipitation slightly increase; in the second phase, from 2030 to 2060, there is a sharp increase in temperatures accompanied by a significant reduction in precipitation.

In addition to the time-invariant climate variables, we use a number of additional exogenous variables to explain land allocation. Distance to Tel Aviv, the dominant business center of the country, represents transportation costs and availability of purchased inputs and services, as well as alternative non-farm employment opportunities available to farm families (Kimhi and Menahem, 2010). Dummy variables of the type of community (Moshav and private communities; Kibbutz is the reference base category) represent the decision-making process and level of cooperation within each community (Kimhi, 1998). Year of establishment of the community represents the different periods in which villages were established, which represent their historical access to resources. Dummy variable indicating whether agricultural land is dominated by light soils stands for the suitability of farmland to the different crops. Water is a public property in Israel, and per-village total irrigation quotas are set administratively by the authorities; these quotas are introduced to capture the impact of water availability on agricultural production. Land uses in Israel are also centrally managed. The total agricultural land owned by the community represents the potential of crop diversification, which is expected to be higher in communities with more land due to potential diseconomies of land fragmentation and economies of scale. The last group of variables includes price indices. As evidenced by official data (IMARD, 2011), prices are homogeneous across Israel. We therefore use country-wide annual output price indices (ρ_j) obtained from the Israel Central Bureau of Statistics (ICBS) for each of the three crop bundles over the sample years. Following Kaminski, Kan and Fleischer (2013) we used lagged moving averages to reflect farmers' price expectations that are used in their land-use decisions. Since land shares of field crops and vegetables can be adjusted from year to year, their price indices were constructed based on the two previous years; for fruits the previous four years were used.[4] Finally, we include the previous-year annual price index of purchased agricultural inputs (w) relevant for the vegetative sector (Kislev and Vaksin, 2003). Note that in the 1992-2002 panel data, only water quotas vary over time and across communities, whereas climate variables and other farm characteristics are time-invariant, and prices are spatially-invariant.

For the simulations we need country-wide data to obtain aggregate supply, production costs and demand-function parameters in the base period, which is represented by the year 2000. We use ICBS data on agricultural lands (L^{kj}), and obtained from cost-and-return studies (IMARD) per-hectare explicit costs (c^{kj}),[5] annual outputs (Q_1^{kj}) and average prices (p_1^{kj}) of the main crops in the three crop bundles; the demand elasticity parameters (β^{kj}), are taken from Hadas (2001). The partial equilibrium simulations take into account the changes in the prices of vegetables and fruits, but not in those of field crops, since the latter are not subject to trade restrictions, are currently imported to Israel, and hence for which changes in local consumption can be met by changes in imports. Figure 2 presents demand curves based on the calibrated $\phi_j^q\left(\phi_j^p\right)$ functions.

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[4] The number of lags was determined after ARIMA estimations using R² and Akaike-Schwartz information criteria.

[5] For consistency with the estimated coefficients $\mathbf{V}_j = \left(a\mathbf{b}_j, -a\left(\gamma_j - \gamma_J\right), -a\left(\delta_j - \delta_J\right)\right)$ we computed c^{kj} while subtracting the overhead assigned in the cost-and-return studies to the non-cultivated agricultural lands; i.e., the reference bundle.

As aforementioned, our analysis assumes partial equilibrium in the base year (2000). According to Finkelshtain, Kahel and Rubin (2011), the local prices of vegetables and fruits are generally similar to their corresponding world prices. Therefore, the import of these goods to Israel is negligible due to the presence of high import tariffs. We calculated the average import price for the bundles of vegetables and fruits, weighted by crop-production quantities, and use these averages as the upper limit of prices ($\bar{\phi}_t^p$) in the simulations (Eq. 11). The calculated average import prices are higher by 36% and 23% than the average local prices for vegetables and fruits, respectively. Table 3 presents country-wide agricultural land use, revenue, costs and profits in the base year of the simulations.

5. Estimation Results

We employed the Stata fractional multinomial logit command (-æ ºłÆŁ-) for estimating the coefficients $\mathbf{V}_j$ for the three bundles, through maximization of the quasi likelihood function in Eq. (6). To control for potential spatiotemporal autocorrelations in the residuals, we clustered observations according to years and 60 *natural* regions (determined by the ICBS (2010) based on criteria such as topography, climate, demography and history).[6] The estimated coefficients are reported in Table 4.

Interpretation of the estimation results is facilitated by Table 5, which presents the marginal effects of the explanatory variables on optimal land shares and profits.[7]

With respect to land-use, both precipitation and degree days have positive and significant marginal effects on the share of non-cultivated land, implying that farmers in wetter and warmer regions benefit from devoting more arable land to agricultural production-support uses. Water quotas exhibit the same effect, possibly due to irrigation equipment and infrastructure being more land consuming, whereas the share of the non-cultivated areas declines with total agricultural land, as expected. Regarding farm profits, farmers residing in younger communities face lower profits. The same holds for Moshavim. The profit of all bundles declines under warmer conditions. The output value of fruits increases with precipitation, whereas farmers that grow vegetables and field crops under dryer conditions obtain larger production values. These effects reflect the spatial distribution of production in

[6] These clusters capture those spatial autocorrelations of measurement errors in the dependent and independent variables between communities of the same region that are not necessarily diminishing with Euclidean distance (e.g., as assumed by the Moran's *I* statistic). For example, due to the presence of topographic (and therefore climatic) boundaries (e.g., between valleys and highlands) and intra-regional processing and marketing cooperatives, the correlation in measurement errors between two adjacent communities from different regions may be considerably lower than the correlation of each one of them with remote communities within the region.
[7] Standard errors were estimated using the bootstrap procedure.

Israel, where vegetables and field crops are mainly grown in the southern semi-arid areas, while fruits are more prevalent in the subtropical north. The overall effect of precipitation on profits is positive, yet not statistically significant. The impact of water quotas indicates some substitution between irrigation and precipitation: the revenue of field crops increases with water quotas, while the opposite holds true for fruits. Nevertheless, the overall effect of water quotas on profit is negative. This non-intuitive outcome may stem from a change in water quality that our data cannot account for: [8] due to water shortage, during the sample period many farmers were forced to replace their freshwater allotments by allocations of treated wastewater based on a ratio of 1.2 m^3 of wastewater in return to a cut of 1 m^3 of freshwater quota. Thus, a similar or even lower profitability level could be associated with larger water quotas.

The marginal effects of output and input prices on farm profits enable us to test whether the estimated profit function complies with economic theory. In our specification of a linear per-hectare profit function (Eq. 2), the profits are homogenous of degree one in output and input prices, and are continuous and convex in all prices. In addition, profit functions need to be non-decreasing in output prices and non-increasing in input prices. Table 5 indicates that our estimated profit function complies with these conditions, with statistically significant positive marginal effects of output prices and non-significant marginal effects of input costs.[9]

6. Simulation Results

Using the estimated model we simulate production of the three crop bundles, where, ceteris paribus, climate variables change as forecasted by Krichak et al. (2011). The simulations encompass the period 2000-2060, where the climate faced by each community in each year is represented by the averages of degree days and precipitation in the previous 20-years.[10] As the predicted responses to temporal changes in climate variables are based on the spatial variations of these variables across communities, the larger the spatial variability in comparison to the temporal variation, the larger the validity of the simulation predictions for future years; in our case, the spatial variance between communities captures 85% and 58% of the total spatiotemporal variance of precipitation and degree days, respectively.

[8] Our data include only the total water quota, without specifications of water qualities.
[9] The linear specification of the profit function in Eq. (2) implies that the condition of the Hessian matrix being positive semi-definite is redundant.
[10] These 20-year moving averages enable to draw trends of changes along the simulation period; however, one should recall that farmers may not adapt on an annual basis, particularly with respect to fruits.

We compare the simulation results obtained under two trade policy scenarios: a *free trade* scenario, where prices of all agricultural outputs in our small economy equal their corresponding world prices, which are assumed fixed in the simulations, and a *restricted trade* scenario, where the government imposes import tariffs on vegetable and fruit products (but not on field crops); under the latter scenario price indices of vegetables and fruits were computed by solving Eq. (11).

Figure 3 draws time paths of the price indices of vegetables and fruits, simulated for the case of restricted trade. The two phases of climate-change trends (Figure 1) are well reflected by the trends of prices: the price index of vegetables hikes during the first phase (until about 2030) and then declines, whereas the price-index of fruits starts reacting only in the second phase by climbing until it hits its upper bound near 2050, and imports start at this point.

In Figure 4 we present for the two trade scenarios the time-path indices of the supply ($\phi_j^y(\mathbf{z}_t)$, Eq. 8) and the demand ($\phi_j^q(\phi_{jt}^p)$, Eq. 10); the difference between them represents imports/exports. In view of Eqs. (7) and (8), the supply quantity index of each bundle *j*, $\phi_j^y(\mathbf{z}_t)$, changes due to the impact of climate and prices on two elements: the per-hectare production values ($\phi_{jt}^p\hat{\mathbf{B}}_j\mathbf{x}_{it}$) and the land shares ($\hat{s}_j(\mathbf{z}_{it})$). To assess the impact of these two components we draw in Figure 4 an index of land share ($\hat{s}_{jt}/\hat{s}_{j1}$), computed using Eq. (13); this decomposes $\phi_j^y(\mathbf{z}_t)$ such that the difference $\phi_j^y(\mathbf{z}_t)-\hat{s}_{jt}/\hat{s}_{j1}$ reflects the supply effect of the per-hectare production values above and beyond the effect of the land shares.

In general, the supply-quantity indices of the three bundles exhibit similar trends under the two trade scenarios: the supply of vegetables declines in the first climate-change phase and then increases nearly to its original level, the supply of field crops declines monotonously throughout the simulation period, and the supply of fruits is relatively stable during the first phase and declines in the second phase. Yet, the magnitudes are different: the changes in the prices of vegetables and fruits under the restricted-trade scenario attenuate the absolute changes in the supplies of these crop bundles, whereas the change in the supply of field crops, whose price index is constant, is slightly larger compared with the change under free trade.

The import (equals $\phi_j^q(\phi_{jt}^p)-\phi_j^y(\mathbf{z}_t)$) of field-crop products is expected to increase under both scenarios. The projected imports of vegetables and fruits increases under free trade, but under restricted trade, the import tariffs would effectively ban imports of fruits and vegetables, with the exception of fruits, where imports will start in 2050 despite the tariff.

Examination of the drivers of the supply-index trends reveals that the variations of land shares ($\hat{s}_{jt}/\hat{s}_{j1}$) are considerably smaller than those of the supply, $\phi_j^y(\mathbf{z}_t)$, implying that the bulk of supply changes are driven by changes in per-hectare production values ($\phi_{jt}^p \hat{\mathbf{B}}_j \mathbf{x}_{it}$). As an example, consider the case of fruits under the restricted-trade scenario (Figure 4f): the supply index in 2060 is nearly 40% lower compared to the base year, while the land-share index is almost unchanged. This reinforces the finding by Kaminski, Kan and Fleischer (2013) that the effectiveness of land reallocation as an adaptation mechanism is rather low compared to per-hectare production adjustments. Yet, as will be shown later, land allocations still serve as an important adaptation tool.

Figure 5 plots simulated changes in country-wide profits under the two trade scenarios, as well as changes in consumer surplus and social welfare (made of the sum of farm profits plus consumer surplus) under the restricted-trade scenario.[11] Table 6 reports these changes in terms of present values over the simulated 60-year period.[12] Due to the predicted rise of local output prices of vegetables and fruits (Figure 3), the simulation anticipates a much smaller decline in farmers' total profits under the restricted-trade scenario than under free trade (Figure 5d). These increases in the prices of agricultural products reduce consumer surplus, and thereby lessen the social welfare even though the decrease in social welfare under free trade remains considerably larger than under restricted trade (Table 6). Thus, overlooking the feedback effect of prices exaggerates the simulated economic impacts of climate-change on both farm profits and social welfare.

As aforementioned, although small compared to the per-hectare effects (Figure 4), land allocation constitutes a significant adaptation instrument. In Figure 6 we present the country-wide agricultural profits simulated under the free-trade scenario for two cases: (1) with land-use adaptation, where land is allocated optimally according to Eq. (4), (2) without land-use adaptation, where land shares are kept equal to those of the base year throughout the whole simulation period. Also presented is the difference between these profits, expressed in terms of percentage of the profits under unchanged land shares. The contribution of land-use adjustments to farming profits is minor in the first two decades, but as profits decline over time it increases up to 30%. This simulation also illustrates the advantage of using a structural model, where land share decisions are explicitly specified as maximizing profits.

[11] There are no consumer surplus changes under free trade since prices are held fixed.
[12] A 5% annual discount rate is used.

7. Concluding Remarks

This paper adds two important aspects to the literature on the impact of climate change on agriculture and food prices. First, it controls for corner solutions in the estimation of a structural econometric land-allocation decision model, and thereby enables treatment of disaggregated farmland and community-level data, such that output prices can be considered exogenous. Second, while the impact of climate change on agriculture has already been analyzed by using macro-level general- and partial-equilibrium models combined with programming-based micro-level models, here we link such a macro-level model with an econometric farm-level land-allocation model. This approach has three advantages: (1) it ensures consistency, as the sample used for estimating the model's functions is also used in the simulation of climate change; (2) thereby, the analysis fully accounts for sample heterogeneity in the effects of and the supply responses to changes in climate variables and prices instead of considering representative categories (conducive to aggregation biases); (3) the econometric micro-level model enables testing statistically whether the profit functions specified in the optimization problem of farmers do comply with economic theory.

These analytical contributions can provide policy makers with a more reliable measure of the effects of climate change on agriculture production and food prices, and capable of distinguishing between heterogeneous producers and consumers. This is particularly important as governments and international organizations alike are called upon to revise current policies in order to provide better adaptation options to climate change, and to integrate agricultural policies within a broader set of policies targeting sustainable development and natural resource management (Howden et al., 2007). Furthermore, taking food prices into consideration is extremely important given its relevance to the critical issues of poverty, food security and malnutrition around the world. Indeed, our empirical analysis for the case of Israel shows considerably different results when free-trade conditions are assumed- where local prices are determined by their world counterparts (which are assumed fixed in our simulations)- compared with the more realistic case in which trade is restricted by import tariffs and local prices are therefore determined by the interplay of local supply and demand (as long as local prices are lower than import prices). This difference highlights the need to account for price feedback effects when modeling the impact of climate change on agricultural production.

Agricultural adaptation to climate change calls for governmental interventions because of equity concerns and prioritization (e.g., Lobell et al. 2008). Some of those interventions can be directly identified from the results of this paper, and indicate ways for further research and extensions of this work. First, heterogeneous impacts of climate change on both producer and consumer welfare may call for specific policy attention; e.g., under our specifications consumers are more impacted than producers under restricted trade, but social welfare being overall larger than under free trade. This would suggest that a transfer scheme (e.g. food price consumer subsidies financed by export or production taxes) from producers to consumers could be politically acceptable.

Second, improved adaptation technologies require R&D investments with a public good component. Identification of the channels through which projected profit and consumer welfare losses is useful to promote a "directed technological change" with higher benefit-cost ratio and more effective public and private spending. For example, our simulations predict that, from about 2030 and on, the surpluses of both producers and consumers of fruits in Israel (under the restricted-trade scenario) are going to decline, whereas the effect on the surpluses of vegetable producers and consumers is minor; hence, proactive adaptation efforts should be directed towards fruits. Likewise, specific technology components of the agricultural systems could also be targeted, as done in Kaminski et al. (2013).

Third, our empirical framework can be generalized to derive a broader and integrated assessment of climate change agricultural-related impacts on social welfare by considering agricultural amenities and environmental externalities in the simulations. Upon availability of sufficient valuation studies and applicability of benefit-transfer methods, the impact of climate change on ecosystem services and landscape value through agricultural productivity adjustments and land-use adaptation could be also assessed (see for instance Bateman et al. 2013). This would also require a refinement of the econometric model to enable estimations of intra-growing season input applications and environmental effects such as polluting effluents. In turn, this could change conclusions on the efficiency and equity of climate-change adaptation agricultural policies and public investments since total climate-driven effects on social welfare can significantly differ from those on private consumers and producer surpluses. For instance, the projected conversion of land planted with orchards and field crops into land occupied by vegetable production is presumably coming along with losses in agricultural amenities such as landscape and recreational services (open fields vs. greenhouses and protected crops) as well as increases in the use of polluting inputs and irrigation water.

Finally, the model can also be applied in conjunction to more sophisticated macro models like CGE, and can be used for assessing a range of additional issues associated with agricultural production and policies; for example, the development of production supportive infrastructures and changing agricultural protection policies such as international trade barriers and subsidies.

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Table 1 - Observations and land shares in crop-production portfolios

Portfolio	Number of observations	Land shares[a] Vegetables	Field crops	Fruits	Not cultivated
Fruits	658	0.000	0.000	0.865	0.135
Field crops	47	0.000	0.978	0.000	0.022
Field crops & Fruits	1,311	0.000	0.632	0.328	0.040
Vegetables	54	0.781	0.000	0.000	0.219
Vegetables & Fruits	854	0.314	0.000	0.550	0.136
Vegetables & Field crops	168	0.163	0.827	0.000	0.010
Vegetables, Field crops & Fruits	5,081	0.176	0.598	0.197	0.029
Total	8,173	0.149	0.447	0.330	0.065

a. Weighted by communities' total agricultural land.

Table 2 - Descriptive statistics of the explanatory variables

Variable	Units	Mean	Std.
Precipitation	m/year	0.395	0.086
Degree Days	10^3×C^o/year	4.380	0.013
Distance to Tel-Aviv	km	73.42	41.03
Moshav	dummy	0.510	0.500
Private Community	dummy	0.094	0.292
Foundation Year	year	1946	20.56
Light Soil	dummy	0.576	0.494
Water Quota	m^3/year	1.44×10^6	1.40×10^7
Land	$10^6\times m^2$	6.351	6.049
Vegetables Price Index (ρ_v)	index	0.641	0.083
Field-crops Price Index (ρ_f)	index	0.663	0.081
Fruits Price Index (ρ_p)	index	0.550	0.107
Inputs Price Index (w)	index	0.489	0.100

Table 3 – Country-wide values in the base year (2000)

	Vegetables	Field crops	Fruits	Non-cultivated	Total
Land (hectare)	54,452	194,328	71,889	22,191	342,859
Land Shares	0.159	0.567	0.210	0.065	1.000
Revenue (10^6 \$/year)	717	262	882	0	1,861
Costs (10^6 \$/year)	683	75	269	0	1,027
Profit (10^6 \$/year)	34	187	613	0	835

Table 4 - Estimated coefficients of land share equations (Eq. 6)[a]

Log likelihood	-8782.6		
Wald $\chi^2(84)$	7887.6		
Variable	**Vegetables**	**Field crops**	**Fruits**
$\rho_j \times$ Precipitation	-15.12***	-6.633***	1.034
$\rho_j \times$ Degree.Days	-0.105***	-0.114***	-0.086***
$\rho_j \times$ Dist.Tel-Aviv	-0.011***	-0.019***	-0.003*
$\rho \times$ Found.Year	-0.027***	-0.023***	-0.022***
$\rho_j \times$ Moshav	-1.655***	-2.901***	-1.545***
$\rho_j \times$ Light.Soil	-0.859***	-0.921***	-0.170**
$\rho_j \times$ Water.Quota	-0.134***	-0.106***	-0.505***
$\rho_j \times$ Land	0.106***	0.133***	0.045***
ρ_j	18.09***	16.41***	11.03***
$-w$	0.610	0.844	-0.416
Constant	0.775**	1.791***	1.310***

*** indicates significance at 1%, ** indicates significance at 5%, * indicates significance at 10%

a. The dummy variable for private communities was omitted due to collinearity

Table 5 - Marginal effects[a]

	Land share				Profit			
Variable	**Vegetables**	**Field crops**	**Fruits**	**Non-cultivated**	**Vegetables**	**Field crops**	**Fruits**	**Total**
Precipitation[b]	-0.9652***	-0.4926***	1.2835***	0.1743***	-2.2207***	-2.9359***	2.8090	0.0625
Degree Days	-0.0193	-0.1357***	0.0914***	0.0636***	-0.2198***	-0.9486***	-0.1219	-0.2761***
Distance from Tel-Aviv	0.0001	-0.0024***	0.0020***	0.0004***	-0.0011***	-0.0104***	0.0034	-0.0002
Foundation Year	-0.0005**	-0.0007**	0.0005*	0.0007***	-0.0030***	-0.0086***	-0.0030**	-0.0038***
Moshav	0.0408***	-0.2669***	0.1551***	0.0710***	-0.1237***	-1.3857***	0.0445	-0.2218**
Light Soil	-0.0223***	-0.0973***	0.0992***	0.0204***	-0.1025***	-0.4674***	0.1733	-0.0232
Water Quota	0.0078***	0.0312***	-0.0461***	0.0071***	-0.0070*	0.0226	-0.1853***	-0.0873***
Land	0.0013***	0.0132***	-0.0114***	-0.0031***	0.0114***	0.0647***	-0.0153	0.0062
Vegetables Price Index (ρ_v)	-0.0002	0.0001	0.3241***	0.0000	2.7520***	0.0001	0.2507**	1.1787***
Field-crops Price Index (ρ_f)	0.0008	-0.0029	0.8499***	0.0003	0.0006	7.6742***	0.6574	1.3931***
Fruits Price Index (ρ_p)	-0.0668	-0.2056	-0.7990**	-0.0229	-0.0517	-0.1590	2.9974**	1.3784***
Inputs Price Index (w)	0.0393	0.0887	-0.2515	-0.0183	0.1232	0.5529	-0.6504	-0.0482

*** indicates significance at 1%, ** indicates significance at 5%, * indicates significance at 10%

a. Total marginal effects on revenues (costs) are the sum of bundles' marginal effects, weighted by the bundles' shares in total revenues (costs), computed based on the data in Table 3.

b. Precipitation is measured in relatively large units of m/year so the reported marginal effects are rather large. A 1 standard deviation change in precipitation would be more intuitively appealing and result in more moderate marginal effects.

Table 6 - Present values of simulated country-wide changes in agricultural profit, consumer surplus and social welfare for the period 2000-2060

	Free Trade	Restricted Trade
Agricultural Profit (10^6 \$)	-4,177	-1,281
Agricultural Profit (%)	-25.11	-7.70
Consumer Surplus (10^6 \$)	0	-1,627
Social Welfare (10^6 \$)	-4,177	-2,907

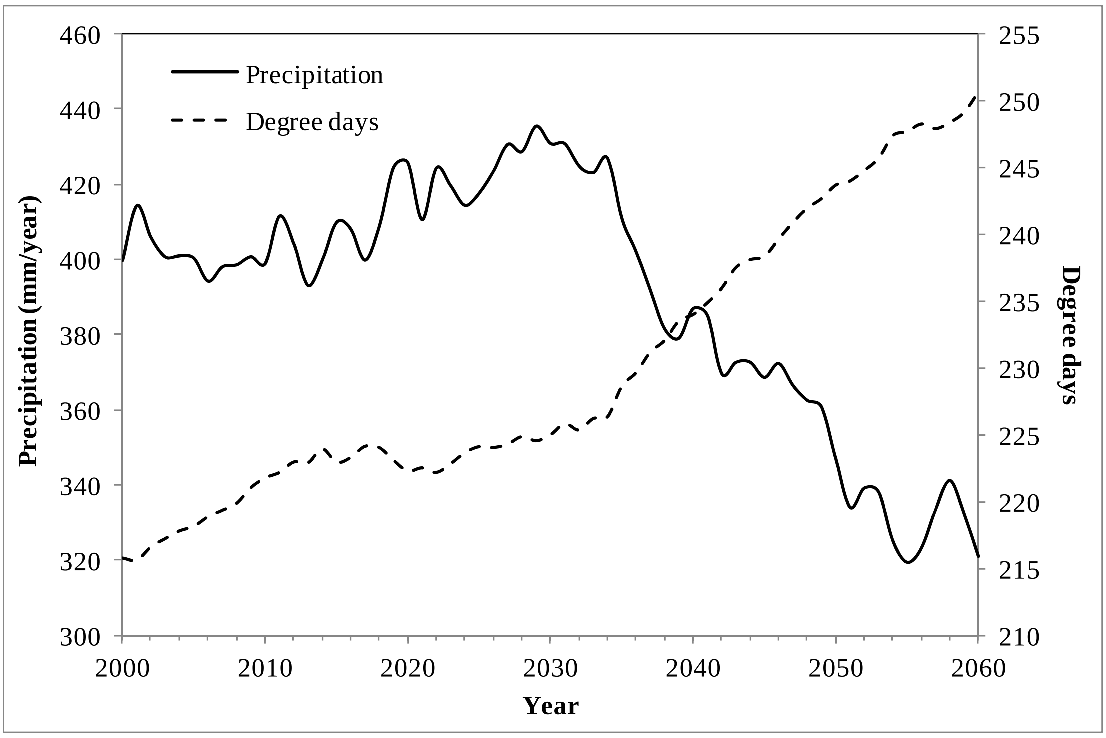

Figure 1 – Moving average of country-wide average annual precipitation and degree days

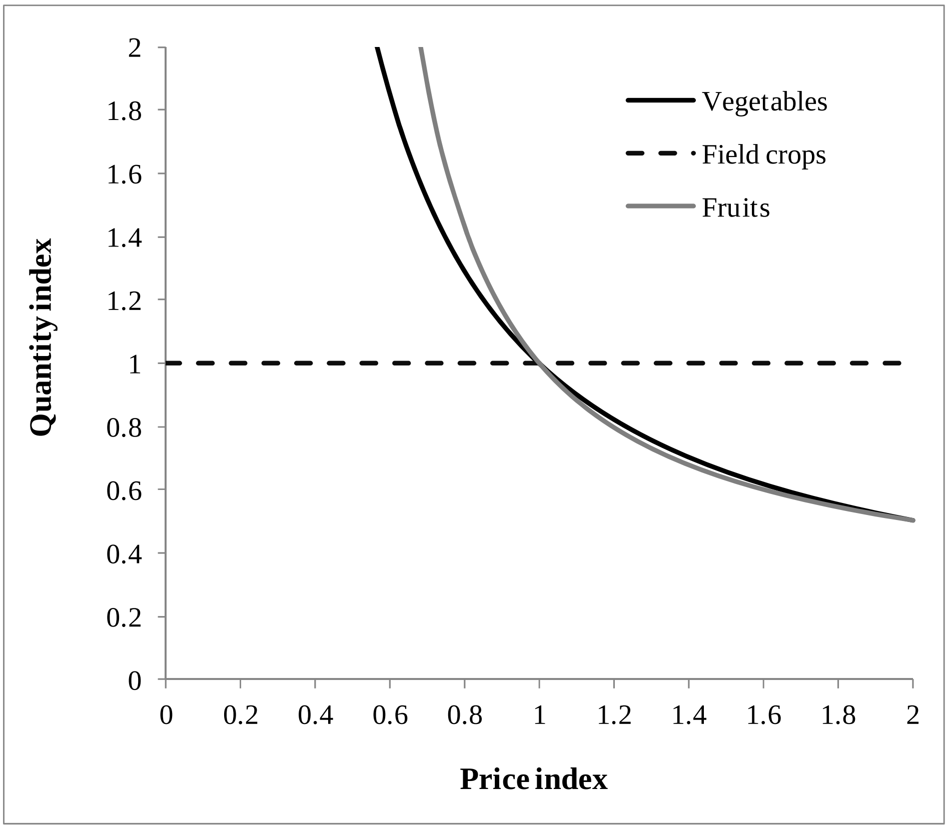

Figure 2 - Demand curves of the different bundles

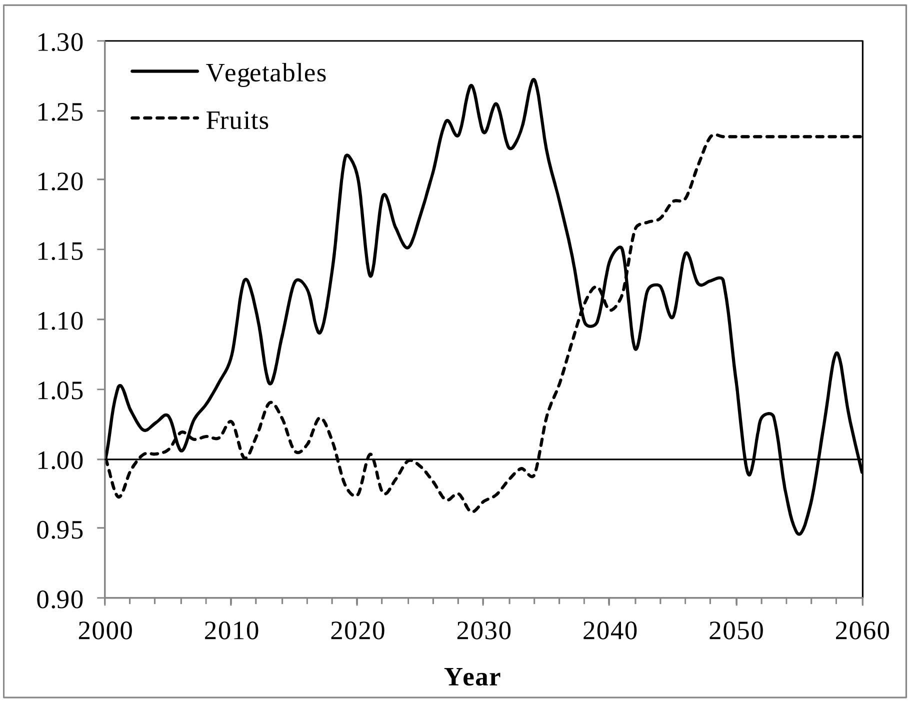

Figure 3 – Simulated time paths of price indices of vegetables and fruits under the restricted-trade scenario

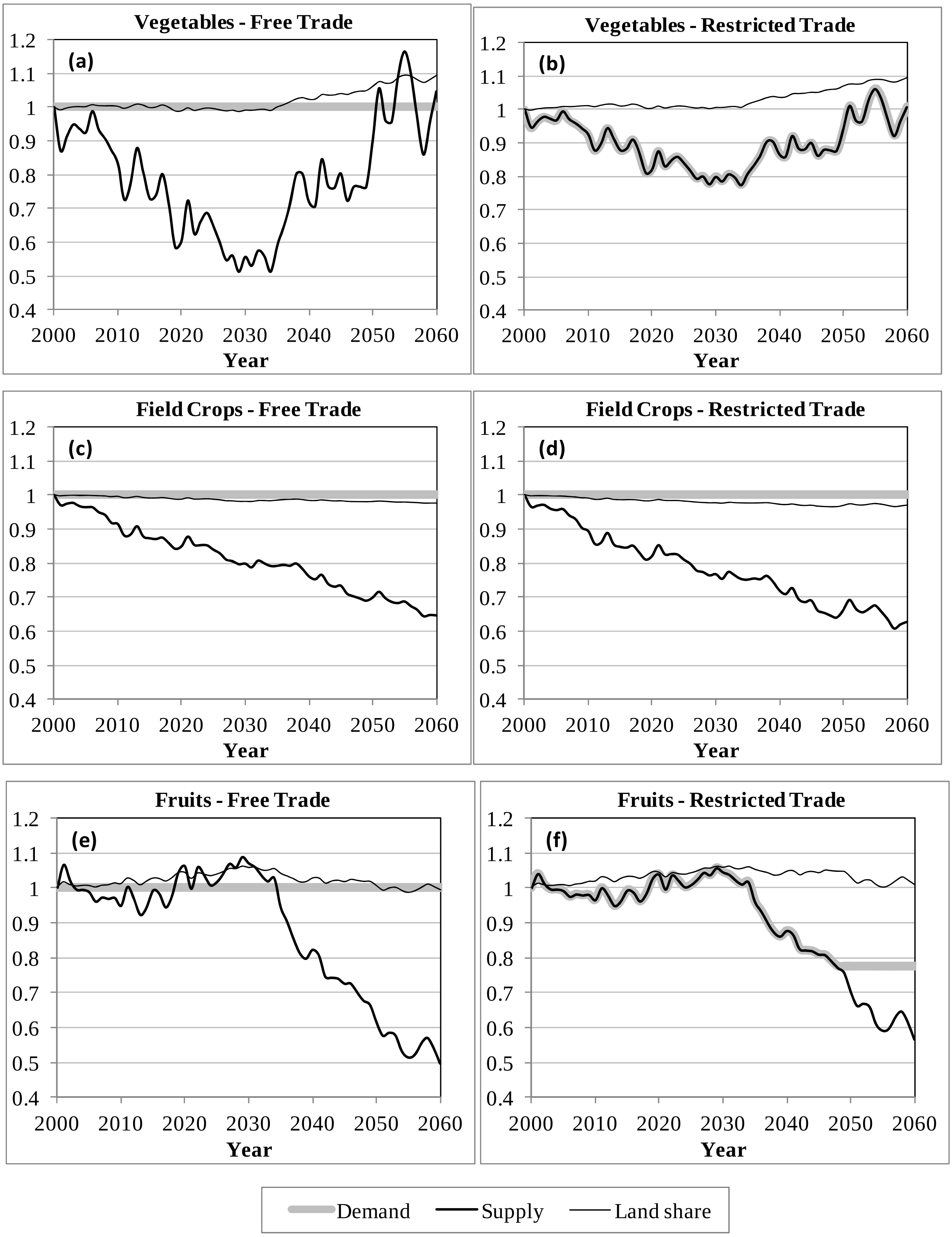

Figure 4 – Indices of demand quantity, supply quantity and land share, simulated under the free- and restricted-trade scenarios

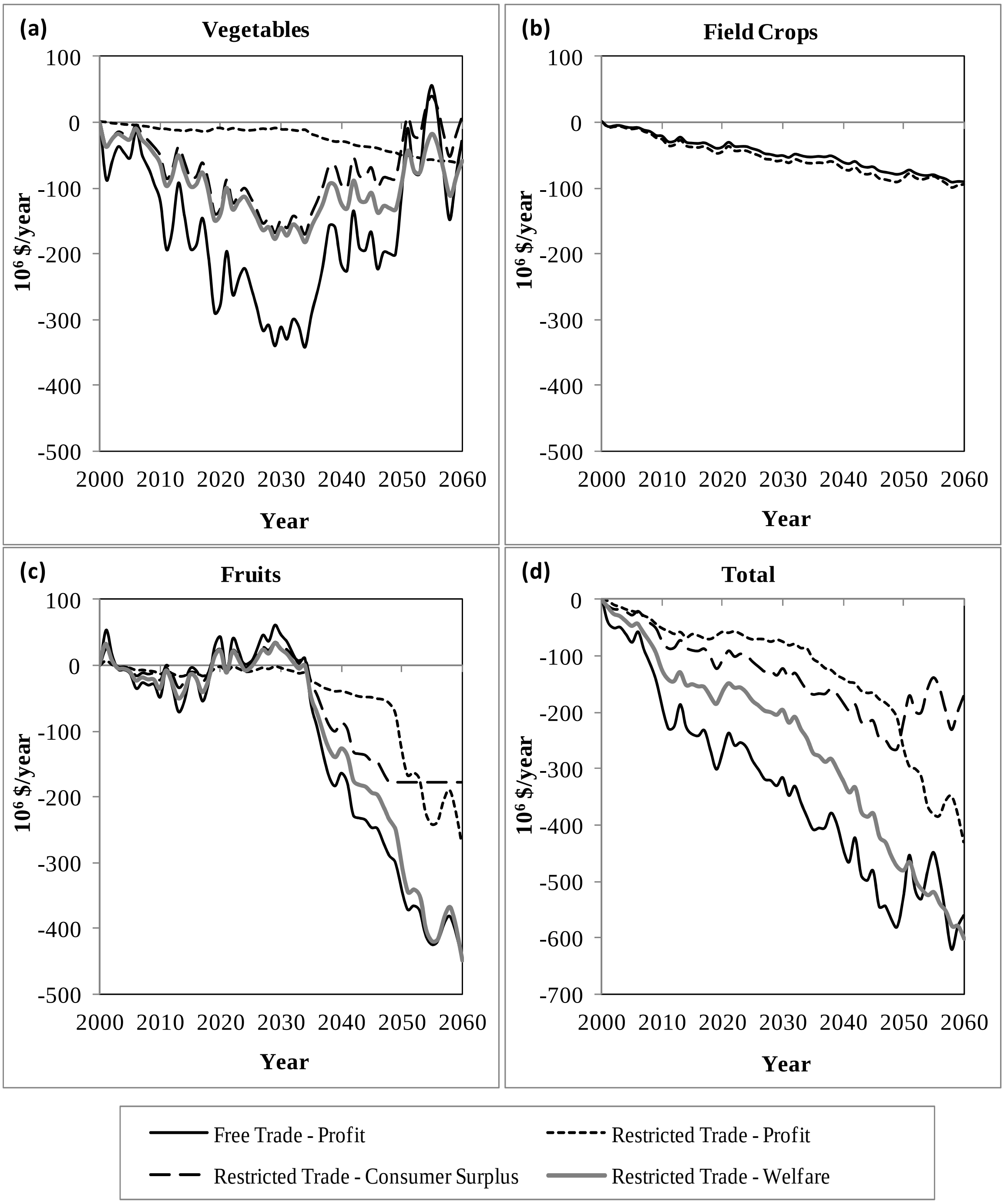

Figure 5 – Simulated country-wide changes in agricultural profits under the free- and restricted-trade scenarios, and in consumer surplus and welfare under the restricted-trade scenario

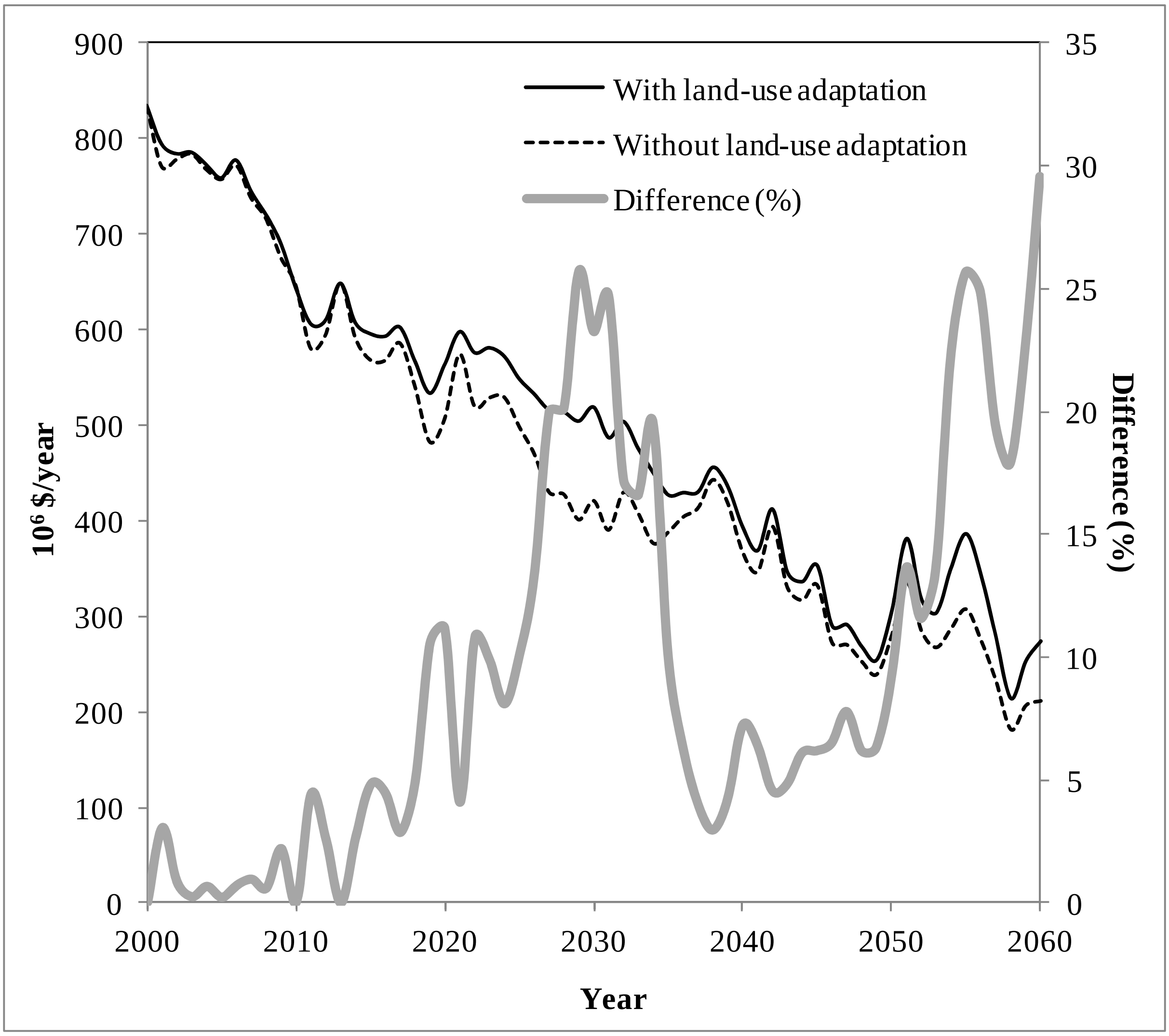

Figure 6 – Contribution of adaptation through land allocation to country-wide agricultural profits under the free-trade scenario.