Integrated Micro-Macro Structural Econometric Framework for Assessing Climate-Change Impacts on Agricultural Production and Food Markets

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This paper combines a micro-level structural econometric model of farmland allocation and a market-level equilibrium supply-demand model in order to simulate the effects of climate changes on agricultural production, food prices and social welfare. The estimation accounts for corner solutions associated with disaggregated land-use data, whose usage enables treating prices as exogenous. We employ the model for assessing climate-change impacts in Israel, in which agriculture is protected by import tariffs. We find that projected climate changes are beneficial to farmers, particularly due to the positive impact of the forecasted temperature rise on field crops. Fruit production are projected to decline, and reduce consumer surpluses, but to a lower extent than the increase in total agricultural profits. Nearly 20% of the profit rise is attributed to farmers' adaptation through land reallocation. Adaptation to the projected reduction in precipitation by increasing irrigation is found warranted from farmers' perspective; however, it is not beneficial to society as a whole. Abolishing import tariffs effectively transfers surpluses from producers to consumers, but its impact on social welfare becomes positive only under large climate changes.

Acknowledegment:

JEL Codes: Q18, Q11

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Key words: climate change; adaptation; agricultural land use; structural analysis; agricultural support policies

JEL Codes: Q15, Q18, Q11

Introduction

Owing to their ability to capture economic interactions among quantities and prices of multiple products and regions, general and partial equilibrium models have become powerful tools for assessing climate-change effects on agriculture. Such macro-level models are frequently linked with micro-level agricultural production models to represent farmers' optimal responses to changes in exogenous variables, including climate, prices and policy instruments. The micro-level models are often based on the mathematical programming approach, in which agricultural production is represented explicitly, and thereby enables integration with the macro-level equilibrium models to reflect price feedback effects on supply changes (e.g., Howitt et al., 2003; Parry et al., 2004; Nelson et al., 2010; Arndt et al., 2011; Arndt et al., 2012; Palatnik et al., 2011; Robinson et al., 2012; Shrestha et al., 2013). The agricultural production functions in such micro-level models are usually calibrated, or derived from estimates external to the model (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 analysis may not capture the sample heterogeneity present in the data with regard to farmers' productivity and production decisions. This paper develops a structural econometric framework for estimating a micro-level supply model which is consistently linkable to a macro-level market-equilibrium model.

Two types of econometric models are widely used in economic analyses of climate change, both are based on the notion that observed farm-management practices and profits reflect farmers' optimal responses to external factors, including climate. 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 et al., 2011). The second type of econometric models employs 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. However, both types of models are based on a reduced-form approach; that is, they do not explicitly estimate production functions, and therefore can be linked to macro-level models only implicitly (e.g., Mendelsohn and Nordhaus, 1996).

The structural model developed in this paper builds on the approach suggested by Kaminski et al. (2013). The approach relies on a recursive decision-making process (McGuirk and Mundlak, 1992): farmers allocate land across crop bundles (e.g., fruits, vegetables, field crops) at the beginning of the growing season based on their anticipated end-of-season optimal per-hectare profits, which are themselves 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 leads to spatial variation in the anticipated relative optimal profitability of bundles, which in turn dictates the observed spatial variation in land allocation across crop bundles. The structure of the profit function enables us to use disaggregated crop-acreage data in combination with aggregate production quantities for estimating per-hectare production and cost functions, as well as testing whether the estimated profit functions comply with economic theory. Utilizing land-use data as opposed to land values allows us to avoid making assumptions regarding the presence of perfect markets for land and other inputs, which are common in the applications of the Ricardian/Hedonic approach. More important for the purpose of this study, agricultural production and output prices are expressed explicitly in the estimated model; this key property is exploited to consistently link this structural econometric micro-level supply model with a macro-level demand model. Consistency between the models is achieved by constraining the estimated coefficients of the micro-level model, such that the aggregate output-value shares of the various crops derived from the model would be equal to the observed output-value shares. Then, in simulations of exogenous changes, the two models feed into each other to determine the equilibrium quantities and prices of agricultural products, while capturing the heterogeneous supply responses in the entire sample used for estimating the micro-level model.

Our analysis deviates from the modeling strategy suggested by Kaminski et al. (2013) in two important aspects. First, by using regional land-allocation data, Kaminski et al. (2013) avoided the need to deal with corner solutions (land shares of 0 or 1). However, because output prices may be endogenous at the regional level, such a strategy would not be suitable for our purposes. Our analysis uses disaggregated data at the community level, where prices can be more safely considered as exogenous. This, however, requires us to use an estimation strategy that controls for the presence of non-negligible number of observations with corner solutions. Second, Kaminski et al. (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 supply model to a macro-level demand model, and simulate partial equilibria. Thus, prices are exogenous in the estimation of micro-level production decisions, but become endogenous in the simulations under partial-equilibrium conditions. The importance of allowing prices to be endogenous in the assessment of climate-change impacts has been highlighted by Fernández and Blanco (2015). Miao et al. (2016) have shown that ignoring the price effects of climate change may lead to an overestimation of the yield effects.

The suggested methodology can be applied to various levels of spatial scales, employing partial- or general-equilibrium frameworks, wherein the prices of different crop bundles can be considered either exogenous or endogenous in the simulations. This feature enables using the model for analyzing the impacts of agricultural support policies, particularly those affecting international trade, that are a subject for continuous debate (see Matthews, 2014): in countries employing trade barriers such as import tariffs, the price of some crop bundles may be determined by equilibrium conditions in the local market, whereas in small open economies prices are set in the global markets and hence are exogenous to the local market. In addition, our methodology can be used to derive local impacts of climate changes, which could be useful for spatially targeted policy responses (De Pinto et al., 2016).

We illustrate our approach using Israeli data, assessing the impact of protective tariffs on the Israeli vegetative agriculture markets under climate change. Israel is particularly suitable for studying the impact of climate change on agriculture because of its diversified climate conditions, within a relatively small distance, from subtropical in the north to arid in the south. In addition, Israeli agriculture is technologically advanced, and has enjoyed decades of experience of adaptation to 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-level 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 et al. (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 might lead to considerable biases 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 within local markets. Therefore, a partial equilibrium model, in which prices are determined endogenously, is 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 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 changes in precipitation and temperature as projected under the various climate-change scenarios adopted by the IPCC (IPCC 2014) in order to simulate changes in farmland allocations, agricultural production, output prices and producer and consumer surpluses. Our results point at positive impacts of the projected climate changes on the Israeli farming sector. These benefits are attributed to increased production of vegetables and field crops. On the other hand, fruit production is expected to shrink, entailing price increase up to the level where protection by import tariffs becomes ineffective. Consequently, local consumers of agricultural products face losses of surplus. However, the overall benefits to farmers exceed the losses to consumers, implying social welfare gains. We find the forecasted sharp temperature rise driving these results, with moderate counterbalance by the projected slight precipitation decline.

We compare the above results to the case where import tariffs are abolished. This policy transfers surpluses from producers to consumers, and we find that social welfare increases only under large enough climate changes. We further show how the model can incorporate farmers' adaptation through input-application changes, as well as to account for changes in prices and availability of inputs. Specifically, we find that offsetting the effect of precipitation reduction by increasing irrigation is an optimal strategy from the farmers' perspective, but not from the point of view of the society as a whole.

In the next two sections we describe the micro-level supply model and the link to the macro-level partial equilibrium model. We then present the data sources and the empirical results, including the estimation of the land-use supply model and the simulations of climate-change impacts on profits and consumer surplus. The final section discuses policy implications and potential extensions.

Supply Model

We model a vegetative agricultural sector that operates in a small economy where all goods are freely traded, except for a subgroup of agricultural products that are subject to import tariffs. Consider a sample of *I* farms where each farm *i*, $i = 1,\ldots,I$, can grow *J* potential bundles of crops (i.e., groups of field crops, vegetables, etc.). Let s_{ji} be the land share of crop bundle *j*, $j = 1,\ldots,J$, in farm *i*. The objective of some farmer *i* is to choose at the onset of the growing season the vector of land shares $\mathbf{s}_i$, $\mathbf{s}_i = (s_{1i},\ldots,s_{Ji})$, so as to maximize the farm's anticipated end-of-season profit:

$$\max_{\mathbf{s}_i} \Pi_i = \sum_{j=1}^{J} s_{ji}\left(\rho_j y_{ji} - c_{ji}\right) - c\left(\mathbf{s}_i\right) \tag{1}$$
$$\text{s.t.} \quad \sum_{j=1}^{J} s_{ji} = 1 \text{ and } s_{ji} \geq 0 \quad \forall\, j = 1,\ldots,J$$

where Π_i is farm-*i*'s economic profit (normalized to per-one-hectare profit), ρ_j is the bundle's expected output price, y_{ji} is the farm-specific expected end-of-season per-hectare optimal yield of bundle *j*, and c_{ji} stands for the expected end-of-season bundle-specific per-hectare optimal economic costs. Both y_{ji} and c_{ji} are anticipated by the farmer while accounting for bundle-specific per-hectare profit-maximization measures she expects to apply during the growing season (i.e., irrigation, fertilization, pesticides, herbicides, etc.) in response to foreseen exogenous events, the likelihood of which depends on various conditions including climate. The function $c(\mathbf{s}_i)$ is the implicit production and management-cost function, representing costs that are neither bundle-specific, nor independent across bundles; for example, $c(\mathbf{s}_i)$ incorporates risks, 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 $c(\mathbf{s}_i)$ captures the constraints on farmers' acreage decisions as motives for bundle diversification and represents the non-linear effects of the allocative land-use variables **s** on farm profits – a pivotal feature in positive mathematical programming (Howitt, 1995).

We further specify the expected optimal per-hectare output of each bundle *j* by the linear function $y_{ji} = \mathbf{b}_j \mathbf{x}_i$, where $\mathbf{b}_j$ is a vector of coefficients, and $\mathbf{x}_i$ is a set of farm-specific yield-related exogenous variables, including climate variables and farm characteristics.[1] The expected optimal bundle-specific economic costs are specified by $c_{ji} = \boldsymbol{\gamma}_j \mathbf{w}_i$, where $\mathbf{w}_i$ is a vector of cost-attributable exogenous variables and $\boldsymbol{\gamma}_j$ is the corresponding vector of coefficients. Thus, the expected maximum per-hectare economic profit of bundle *j* is:

$$y_{ji}\rho_j - c_{ji} = \mathbf{b}_j \mathbf{x}_i \rho_j - \boldsymbol{\gamma}_j \mathbf{w}_i \equiv \mathbf{v}_j \mathbf{z}_{ji} \tag{2}$$

where $\mathbf{v}_j = (\mathbf{b}_j, -\boldsymbol{\gamma}_j)$ and $\mathbf{z}_{ji} = (\mathbf{x}_i \rho_j, \mathbf{w}_i)$. Noteworthy, since $\boldsymbol{\gamma}_j \mathbf{w}_i$ incorporates the shadow values of constrained factors, it expresses the per-hectare economic costs rather than the explicit costs reported in bookkeeping records; hence, $\mathbf{v}_j \mathbf{z}_{ji}$ represents the per-hectare economic profit rather than the accounting profit. Also note that the vector of exogenous variables $\mathbf{z}_{ji}$ being bundle-specific due to the multiplication of the variables in $\mathbf{x}_i$ by the respective output price 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 $c(\mathbf{s}_i)$ 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 (2014) and Kaminski et al. (2013) assume the opposite-entropy function:

$$c(\mathbf{s}_i) = \frac{1}{a} \sum_{j=1}^{J} s_{ji} \ln(s_{ji}) \tag{3}$$

where the a parameter, measured in land-per-money units (and therefore assumed positive), reflects the "weight" of the implicit costs in the economic-profit function. This is a negative, non-monotonic convex function with respect to s_{ji}. The non-monotonicity implies that, ceteris paribus, the implicit costs decline with s_{ji} for $\exp(-1) \geq s_{ji} \geq 0$, and increase with s_{ji} when $1 \geq s_{ji} > \exp(-1)$. Since land shares are negatively correlated among themselves through the land constraint, $c(\mathbf{s}_i)$ reaches its minimum value when $s_{ji} = 1/J$ for all $j = 1,\ldots,J$.

Deriving the optimal solution from problem (1) above, given the per-hectare optimal expected profit specification (2) and the opposite-entropy specification (3) for $c(\mathbf{s}_i)$, yields the following multinomial logit functional form for the optimal land shares (see Appendix A):

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

where $s_j^*(\mathbf{z}_i)$ is the profit-maximizing land share of bundle j, and $\mathbf{z}_i \equiv (\mathbf{z}_{1i},\ldots,\mathbf{z}_{Ji})$.

The land constraint implies that the parameters of only $J-1$ bundles can be identified; we specify bundle J as the reference bundle. 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, and treat these supportive lands as the reference bundle. As in crop cost-and-return studies (e.g., see studies by UC Davis), the revenue contribution of the supportive lands is reflected only through the cultivated areas; that is, $\mathbf{b}_J = 0$. We divide and multiply s_{ji}^* in Eq. (4) by $\exp(a\mathbf{v}_J z_{Ji})$ to obtain

$$s_{ji}^{*}(\mathbf{z}_i) = \exp(\mathbf{V}_j \mathbf{z}_{ji}) \left(\sum_{j=1}^{J} \exp(\mathbf{V}_j \mathbf{z}_{ji}) \right)^{-1} \quad (5)$$

where $\mathbf{V}_j = \left(a\mathbf{b}_j, -a(\boldsymbol{\gamma}_j - \boldsymbol{\gamma}_J)\right) \equiv (\mathbf{B}_j, \mathbf{G}_j)$; this implies that we cannot identify a and $\mathbf{v}_j$, but only the coefficients $\mathbf{B}_j$ and $\mathbf{G}_j$ in $\mathbf{V}_j$.

One could use Eq. (5) to obtain a system of $J-1$ linear land-share regression equations.[2] Indeed, being conveniently estimable due to linearity, flexible, and 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., Wu and Segerson, 1995; Hardie and Parks, 1997; Miller and Plantinga, 1999). However, the set of linear regression equations derived by the multinomial logit specification cannot treat corner solutions (i.e., land shares of 0 or 1). This limitation may not emerge when estimation is based on regionally aggregated data, where zero land-share observations are rare; but at the regional level prices may be endogenous. Our disaggregated land-use dataset discards the endogeneity of prices,[3] but on the other hand may involve a non-negligible number of observations with corner solutions. Hence, we estimate Eq. (5) by employing the quasi maximum-likelihood approach to the fractional multinomial logit likelihood function (Papke and Wooldridge, 1996; Buis, 2010):

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

where s_{ji} is the observed land share, and $s_{ji}^{*}(\mathbf{z}_i)$ is as specified in Eq. (5).

The land-use model developed thus far can be transformed into a supply model using the per-hectare profit-maximizing yield function $y_{ji} = \mathbf{b}_j \mathbf{x}_i$, such that the predicted total production of bundle *j* by farm *i* is $l_i s_{ji}^{*}(\mathbf{z}_i)\mathbf{b}_j \mathbf{x}_i$, where l_i is the total land area of farm *i*. Two obstacles emerge: first, output data are frequently available only at the macro level (e.g., for the entire country); second, the coefficients $\mathbf{b}_j$ cannot be separated from the *a* parameter.[4] We handle these limitations by referring to production outputs in relative terms and by utilizing aggregate information as a constraint in the estimation of the land-use model. Let the sample's total production value of bundle *j* be

$$A_j(\mathbf{z}) = a\rho_j \sum_{i=1}^{I} l_i s_j^*(\mathbf{z}_i)\mathbf{b}_j \mathbf{x}_i \tag{7}$$

where $\mathbf{z} \equiv (\mathbf{z}_1, ..., \mathbf{z}_I)$. Let bundle 1 be the reference, and denote by r_j the observed ratio of the aggregate country-wide production values of bundle *j* and bundle 1. We estimate Eq. (6) subject to the set of constraints

$$\frac{A_j(\mathbf{z})}{A_1(\mathbf{z})} = r_j \;\; \forall\, j = 2, ..., J-1 \tag{8}$$

It is easily seen that the parameter *a* in Eq. (7) is canceled out in Eq. (8). The additional benefit is that we can use the aggregate information embedded in the ratios r_j, $j = 2, ..., J-1$, to assign a meaningful production interpretation to the coefficients $\mathbf{b}_j$.

Linking Micro- and Macro-Level Models

The aggregate production value of bundle *j*, $A_j(\mathbf{z})$, also serves as the link between the micro-level supply model and the macro-level demand model. Let $\phi_{jt}^p = \rho_{jt}/\rho_{j1}$ denote the simulated output-price index of crop bundle *j* at some year *t* relative to year 1 (the base year,), so that ϕ_{j1}^p is normalized to 1. We define a vector of price indices $\boldsymbol{\phi}_t^p = (\phi_{1t}^p, ..., \phi_{J-1t}^p)$, and the corresponding set of explanatory variables $\mathbf{z}_{ijt} = (\phi_{jt}^p \rho_{j1} \mathbf{x}_{it}, \mathbf{w}_{it})$ for every farm $i = 1, ..., I$, bundle $j = 1, ..., J-1$, and year *t*, where $\mathbf{x}_{it}$ and $\mathbf{w}_{it}$ incorporate the values (observed for $t = 1$, forecasted for $t > 1$) of farm-*i*'s variables at year *t*. Accordingly, $\hat{s}_j^*(\mathbf{z}_{it})$ is the predicted land share calculated by Eq. (5) given the year-t's set of variables $\mathbf{z}_{it} = \left(\mathbf{z}_{ijt}, \ldots, \mathbf{z}_{iJ-1t}\right)$ and the estimated coefficients $\hat{\mathbf{B}}_j$ and $\hat{\mathbf{G}}_j$. Then, the aggregate optimal output value for each bundle j is predicted by $\hat{A}_j\left(\mathbf{z}_t\right) = \phi_{jt}^p \rho_j \sum_{i=1}^{I} l_i \hat{s}_j^*\left(\mathbf{z}_{it}\right) \hat{\mathbf{B}}_j \mathbf{x}_{it}$, where $\mathbf{z}_t = \left(\mathbf{z}_{1t}, \ldots, \mathbf{z}_{It}\right)$. 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:

$$\phi_j^y\left(\mathbf{z}_t\right) = \frac{\hat{A}_j\left(\mathbf{z}_t\right)}{\hat{A}_j\left(\mathbf{z}_1\right)} \tag{9}$$

The quantity index $\phi_j^y\left(\mathbf{z}_t\right)$ depends on the output-price index ϕ_{jt}^p directly through the impact on the output value $\hat{A}_j\left(\mathbf{z}_t\right)$, as well as indirectly through the effect on $\mathbf{z}_t$, which entails land-use adaptation responses. Note that the parameter a vanishes in Eq. (9) as well, thereby enabling to simulate changes in the supply index based on $\hat{\mathbf{B}}_j$ without the need to identify a and $\mathbf{b}_j$.

We now turn to the demand side. Similar to the supply side, we formulate a bundle quantity index as a function of price indices, which is based on aggregate country-wide data 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, $j = 1, \ldots, J-1$, is identical and equal to K. Denote the price of crop k, $k = 1, \ldots, K$, of bundle j in year t as p_t^{kj}, and the aggregate quantity of this crop demanded by local consumers as Q_t^{kj}. Also assume that the country-wide aggregate demand function is of the constant-elasticity form:

$$Q_t^{kj} = h^{kj} \cdot \left(p_t^{kj}\right)^{\beta^{kj}} \tag{10}$$

where β^{kj} is a known demand elasticity and h^{kj} is a calibrated parameter. Assume further that all crops in each bundle *j* satisfy the criteria of a composite commodity; that is, their prices change proportionately.[5] Define the *Laspeyres* demanded-quantity index, ϕ_{jt}^{q}, which based on Eq. (10) becomes a function of the simulated price index ϕ_{jt}^{p}, as:

$$\phi_j^q\left(\phi_{jt}^p\right)=\frac{\sum_{k=1}^{K}p_1^{kj}h^{kj}(\phi_{jt}^p p_1^{kj})^{\beta^{kj}}}{\sum_{k=1}^{K}p_1^{kj}Q_1^{kj}} \tag{11}$$

If the markets for bundle-*j* products are in equilibrium in the base period ($t=1$), then $\phi_j^q\left(\phi_{j1}^p\right)=\phi_j^y\left(\mathbf{z}_1\right)=1$. 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. (9) breaches the equilibrium. Without trade restrictions, prices change only if world prices change,[6] and the gap between the demand quantity index $\phi_j^q\left(\phi_{jt}^p\right)$ and the supply quantity index $\phi_j^y\left(\mathbf{z}_t\right)$ represents the change in import or export of bundle-*j*'s products. If trade is restricted by import tariffs, the set of local price indices $\boldsymbol{\phi}_t^p$ would change so as to meet equilibrium conditions in the local markets, unless price changes are large enough so as to turn import-tariff restrictions ineffective. Let $\bar{\boldsymbol{\phi}}^p=\left(\bar{\phi}_1^p,...,\bar{\phi}_{J-1}^p\right)$ be the set of import prices, which equals the world prices plus the country's import tariffs. We simulate partial equilibrium by solving

$$\begin{aligned}&\min_{\boldsymbol{\phi}_t^p}\sum_{j=1}^{J-1}\left(\phi_j^q\left(\phi_{jt}^p\right)-\phi_j^y\left(\mathbf{z}_t\right)\right)^2\\&s.t.\ \boldsymbol{\phi}_t^p\le\bar{\boldsymbol{\phi}}^p\end{aligned} \tag{12}$$

Eq. (12) links the supply quantity index, which incorporates all the sample data points, to the demand quantity index, which is based on aggregate data, while taking into account trade restrictions through the implementation of import tariffs.

The model provides the information required for calculating changes in welfare elements. The change in consumer surplus from the base period to some year *t* is computable for every bundle *j*, $j = 1, \ldots, J - 1$, based on Eq. (10): $\Delta CS_{jt} = \sum_{k=1}^{K} \frac{h^{kj}}{\beta^{kj}+1}\left[(\phi_{jt}^{p})^{\beta^{kj}+1} - 1 \right] (p_1^{kj})^{\beta^{kj}+1}$.

Aggregate local-farming revenues and imports at time *t* are given by $\phi_j^y\left(\mathbf{z}_t\right)\sum_{k=1}^{K} p_1^{kj} Q_1^{kj}$ and $\left[\phi_j^y\left(\mathbf{z}_t\right) - \phi_j^q\left(\phi_{jt}^p\right)\right]\sum_{k=1}^{K} p_1^{kj} Q_1^{kj}$, respectively. To compute local aggregate accounting profits one needs to subtract the explicit costs from the production value. However, as aforementioned, the estimated economic-cost function $\mathbf{G}_j \mathbf{w}_i$ differs from farm-*i*'s explicit costs by the presence of constrained factors multiplied by their respective shadow values. We distinguish between these two types of costs by defining $\mathbf{w}_i^e = \left(w_i^{1e}, \ldots, w_i^{Ne}\right)$ as a subset of $\mathbf{w}_i$ that incorporates those variables associated with explicit costs (e.g., purchased production factors). Accordingly, farm-*i*'s predicted total explicit cost at time *t* is

$$C_{it}\left(\mathbf{z}_{it}\right) = \sum_{j=1}^{J-1} l_i s_{ji}^{*}\left(\mathbf{z}_{it}\right) C_j\left(\mathbf{w}_{it}^{e}\right) \tag{13}$$

where $C_j\left(\mathbf{w}_{it}^e\right)$ is a bundle-specific total per-hectare explicit-costs function, which is derivable from macro-level information and cost-and-return studies. We specify

$$C_j\left(\mathbf{w}_{it}^{e}\right) = L_j^{-1} \sum_{k=1}^{K} L^{kj} C^{kj} \sum_{n=1}^{N} \alpha_n^{kj} \frac{w_{it}^{ne}}{w_{i1}^{ne}} \tag{14}$$

where L^{kj} is the country-wide aggregate land allocated to crop *k* in bundle *j*; L_j is the aggregate land allocated to bundle *j* such that $L_j = \sum_{k=1}^{K} L^{kj}$; C^{kj} is the per-hectare production costs of crop k in bundle j; α_n^{kj} is the share of explicit-cost item n, $n = 1,...,N$, in C^{kj}, and w_{it}^{ne} is the level of farm-i's explicit-cost variable n at time t. Noteworthy, the explicit costs can serve as an additional link between the micro-level supply model and macro-level input-demand models so as to treat input-prices endogenously.

Data and Variables

Our dataset for estimating the micro-level land-allocation model is a panel of 7,569 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).[7] Altogether the sample covers 264,000 hectares per year—more than 60% of the agricultural land 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 her 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 aggregate land shares of four crop bundles: vegetables, field crops, fruits, and the reference bundle of non-cultivated land. In Table 1 we present the number of observations and average land shares (weighted by total community agricultural land) of the 8 different portfolios of crop bundles. In only 62% of the observations land is allocated to all three crop bundles; this highlights the need to account for corner solutions in the estimation procedure. As expected, the land share of field crops is the largest with 54.7%, ahead of fruits

(26.0%), then vegetables (15.0%), and non-cultivated areas (4.3%); the latter varies across portfolios between 20% in the communities that produce vegetables only, and 2% when production of vegetables is combined with field crops.

Table 1 about here

Table 2 reports sample means and standard deviations of the explanatory variables used in the estimation of the production value (**x** and ρ_j for the three bundles) and cost (**w**) functions. As aforementioned, the interaction of **x** with ρ_j enables to identify the production- and cost-impacts of variables that appear in both **x** and **w**; however, since prices vary only with time, multicollinearity may still emerge. Herein we assign variables to either **x** or **w** based on our preliminary expectations of their dominant impact.

Table 2 about here

Precipitation and temperature data are from reports by the Israeli Meteorological Service (IMS) for 594 and 70 meteorological stations, respectively, covering the entire state of Israel during the years 1981-2002. We assign the data from station locations to the coordinates of each agricultural community in our sample using the Inverse Distance Weighting (IDW) method. We choose the power 1 IDW specification due to its superior robustness (Kurtzman and Kadmon, 1999). The climate variables we use are annual average temperature and cumulative annual precipitation. For each year in the sample we consider the average temperature and precipitation along the previous 10-year period as those that have been considered by farmers in their agricultural land-use decisions.

In the simulations of climate conditions in future periods we use forecasts provided by three Global Circulation Models (GCMs): CCSM4 (Gent et al. 2001), MIROC5 (Watanabe et al. 2010) and NorESM1-M (Bentsen et al. 2013); each GCM provides projections for a representative year in two future periods (2040-2060 and 2060-2080) under each of the four Representative Concentration Pathways (RCP2.6, RPC4.5, RPC6 and RPC8.5) adopted by the

IPCC for its fifth assessment report (IPCC 2014). Table 3 presents the statewide average of the forecasted climate variables. The three models generally predict a considerable increase in average temperature throughout Israel at both future periods, from 19C^{o} up to 25C^{o}. Annual precipitation is expected to slightly decline during 2040-2060, and then decline more sharply during 2060-2080 (by about 14% relative to the base-period level).

Table 3 about here

In addition to the climate variables, we explain production by dummy variables for the type of community (Moshav and private communities; Kibbutz is the reference category), representing the production impacts of decision-making process and level of cooperation within each community (Kimhi, 1998). A dummy variable indicating whether agricultural land is dominated by light soils stands for the suitability of farmland to the different crop bundles. We also include dummy variables for Israel's 19 Ecological Regions (as defined by Israel Central Bureau of Statistics (ICBS)) to capture spatial differences that may affect outputs (e.g., topographic and additional climate variables).

Output prices (ρ_j) are homogeneous across Israel, as evidenced by official data (IMARD, 2011). Hence, we use country-wide annual output price indices reported by the ICBS for each bundle over the sample years. To reflect price differences between bundle outputs we multiply each bundle's price index by the average price of its main crops, $\bar{p}_1^j = \sum_{k=1}^{K} p_1^{kj} Q_1^{kj} \Big/ \sum_{k=1}^{K} Q_1^{kj}$ (recall p_1^{kj} and Q_1^{kj} in Eq. (11)), where p_1^{kj} is taken from cost-and-return studies (IMARD) and Q_1^{kj} is ICBS's data on the crop's country-wide annual output in 2002 (see Appendix B; all monetary values are in terms of US dollars in 2000). Following Kaminski et al. (2013), we use lagged moving averages to reflect price expectations that farmers use when making 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, whereas the previous four years were used for fruits.[8]

The production-value ratios r_j used in Eq. (8) are computed by $r_j = \sum_{k=1}^{K} p_1^{kj} Q_1^{kj} \Big/ \sum_{k=1}^{K} p_1^{k1} Q_1^{k1}$, where Field-crops is used as the reference bundle ($j = 1$).

For the per-hectare cost functions we use the distance to Tel Aviv to represent peripheral effects such as transportation costs and availability of purchased inputs and services, as well as alternative non-farm employment opportunities (Kimhi and Menahem, 2017). Water resources are officially controlled by the state in Israel, and per-village total irrigation-water quotas are set administratively by the authorities; these quotas are introduced to capture the impact of water availability on production costs. Land assignment to farming is also centrally managed in Israel. The total agricultural land owned by the community represents potential diseconomies of land fragmentation and economies of scale. Finally, we include the previous-year annual price index of purchased agricultural inputs that are relevant for the vegetative sector (Kislev and Vaksin, 2003); this variable represents the explicit costs $C_j\left(\mathbf{w}^e\right)$ (recall eq. (13)). To reflect explicit-cost differences across bundles we multiply this price-inputs index by a bundle-specific factor, which is computed by $\sum_{k=1}^{K} L^{kj} C^{kj} \Big/ \sum_{k=1}^{K} L^{kj}$ (recall eq. (14)), where L^{kj} is country-wide agricultural lands (IMARD) and C^{kj} is the per-hectare costs[9] taken from cost-and-return studies (IMARD) (Appendix B).

In addition to the already mentioned data on L^{kj}, C^{kj}, Q_1^{kj} and p_1^{kj}, the macro-level model requires the demand elasticities β^{kj} (Eq. (10)). Israel is a net exporter of vegetables and fruits, whose imports are constrained by import tariffs, and a net importer of field-crop products, which are traded freely. Hence, the output prices faced by growers of vegetables and fruits are affected by both the local and international markets. As our micro-level disaggregated land-use data do not enable distinguishing between production to the local and international markets, we assume constant export shares of 29% and 22% of the total production value of vegetables and fruits, respectively (Finkelshtain et al. 2011).[10] For the local markets of vegetables and fruits we adopt demand-elasticity parameters from Hadas (2001) (Appendix B). Both growers and consumers of field crops face the world prices of field crops; hence, the demand elasticity equals the sum of import demand and local-supply elasticities, weighted by the relative import and local-production quantities. Import demand elasticities, estimated based on the methodology developed by Kee et al. (2008), were taken from the World Bank (2012), and import quantities of field-crop products were obtained from the ICBS (Appendix B). With these elasticities and import values we employ Eq. (12) for simulating import response to price changes, obtaining a field-crops import demand elasticity of -1.60. To calculate the local-supply elasticity we use our estimated micro-level supply model to simulate field-crop production response to a price change, obtaining supply elasticity of 0.55. As local production of field crops constitutes 24% of the total consumption, the demand elasticity equals -1.08. Figure 1 presents the resultant demand curves based on the calibrated $\phi_j^q\left(\phi_j^p\right)$ functions.

Figure 1 about here

As aforementioned, our analysis assumes partial equilibrium in the base period (represented by the year 2000). According to Finkelshtain et al. (2011), the local prices of vegetables and fruits are generally similar to their corresponding world prices. Therefore, imports of vegetables and fruits to Israel are negligible due to the presence of high import tariffs (reported in Appendix B). We calculate 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 ($\overline{\phi}_t^p$) in the simulation of the restricted-trade scenario (Eq. (12)). The calculated average import prices (world prices + import tariffs) are higher by 36% and 23%

than the average local prices for vegetables and fruits, respectively. As to forecasts of world prices, we take the trends projected by Eboli et al. (2010) by the use of a global CGE model.[11]

Estimation Results

We use the Stata fractional multinomial logit command (-æ ºŁÆŁ-) for estimating the coefficients $\mathbf{V}_j$ for the three crop bundles, through maximization of the quasi likelihood function in Eq. (6) subject to the constraints in Eq. (8). We control for potential spatiotemporal autocorrelations in the residuals by clustering observations according to years and 60 *natural* regions.[12] We include quadratic levels of the precipitation, temperature, agricultural land and water-quota variables to capture non-linear responses. The estimated coefficients are reported in Table 4.

Table 4 about here

Interpretation of the estimation results is facilitated by Table 5, where we present the marginal effects of the explanatory variables on optimal land shares and economic profits.[13]

Table 5 about here

On the production side, both precipitation and temperature have positive and significant marginal effects on the overall cultivated land, implying that farmers in wetter and warmer regions benefit from devoting more arable land to agricultural production. These climate variables also positively affect the total economic profit, yet, with different impacts across bundles. Farmers in higher-precipitation areas benefit from growing field crops and fruits more than vegetables; this result is congruent with the relative advantage of the southern arid part of Israel in vegetable production, as mentioned by Fleischer et al. (2008). Recall that the per-hectare expected outputs in our model are associated with anticipated optimal responses of farmers to various events during the growing season. A possible explanation for the relative disadvantage of vegetables in the wetter areas is the enhancement of plant disease by rainfall (see Agrios, G. N., 2005; Burdman and Walcott, 2012). Farmers may apply costly protective inputs so as to obtain profit-maximizing per-hectare yield levels that are lower than those obtainable in the drier regions. Higher temperatures increase field-crops profitability, but reduce profits in fruit cultivation, which may be explained by the deciduous-trees' chilling requirements to bloom.

Moshavim tend to allocate less land to field crops than Kibbutzim and private communities, and their total economic profits in field crops are lower. Light soils are associated with more farmland allocated to fruits and less to vegetables and field crops, and this is also reflected in the profit differentials associated with soil type. Regarding output prices, as expected theoretically, all bundles exhibit statistically significant positive own-price impacts and negative cross-bundle impacts on economic profits.

The marginal effects of the cost variables on total economic profits also exhibit expected signs. Peripheral communities face lower profits, which is explainable by higher transportation costs and lower availability of production factors. Larger irrigation-water quotas increase profitability. However, the effect is statistically insignificant, indicating that water quotas do not constitute effective constraints; this matches the conclusion of Feinerman et al. (2003) that since the early 1990s, agricultural water consumption in Israel was dictated by water prices rather than by water quotas. By examining the water-quotas effects in relation to those of precipitation, we find that irrigation water is a substitute to precipitation in the production of fruits and vegetables, and is a complement to precipitation in field-crops production; this finding coincides with the fact that, while vegetables and fruits are usually irrigated, the field-crops bundle includes both rain-fed and irrigated crops. The positive sign of the community's total agricultural land points at the presence of economies of scale. Finally, prices of production inputs negatively affect total economic profits (although without statistical significance). Thus, the effect of both input and output prices on economic profits complies with economic theory.

Simulations

Using the estimated model we simulate production of the three crop bundles, where, ceteris paribus, climate variables change as reported in Table 2,[14] and world prices vary according to Eboli et al. (2010). That is, we assess the impact of changes in the climate conditions and the associated world prices as if they have occurred at the base period. We study the consequences of these changes under six scenarios with respect to policies and farming adaptation strategies.

Scenario 1 simulates variation in the climate variables under the prevailing policy of constraining trade by use of import tariffs. Tables 6 and 7 report the results in terms of changes relative to the base-period climate, averaged across the three GCMs. All four RCPs for the two future climate periods exhibit similar trends of changes in output prices (ϕ_{jt}^{p}), quantities demanded (ϕ_{jt}^{q}) and supplied (ϕ_{jt}^{y}), and land shares (s_{jt}/s_{j1}) (Table 6). The supplies of vegetables and field crops increase, whereas that of fruits declines. Local output prices of vegetables decline, while those of fruits rise up to their respective upper bound, $\bar{\phi}_{jt}^{p}$; consequently, the demanded quantity of fruits exceeds the local supply such that import emerges. The prices of field crops change marginally with world prices; hence, the demanded quantity remains stable, and the increased supply of field-crop outputs may reduce the imports of field-crop products.

Table 6 about here

By comparing the local supply indices (ϕ_{jt}^{y}) to the land-share indices (s_{jt}/s_{j1}) one can assess the role played by the changes in per-hectare production versus changes in land allocation. The simulations indicate that field-crops productivity is predicted to increase more than two-fold, which in turn leads to expanding the land allocated to field-crop by about 10% at the expense of vegetables and fruits. Per-hectare production of vegetables also increases, but to a lower extent than that of field crops; therefore, the land allocated to vegetables declines. Fruit production declines sharply by about 40-60%, leading to a land-share reduction of about 25%.

Table 7 about here

Table 7 reports changes in aggregate agricultural accounting profits, consumer surplus and their sum (i.e., social welfare) under Scenario 1. Apparently, climate change is generally beneficial to Israeli farmers, particularly to field-crop growers. Vegetable farms also benefit from climate change, but to a much lower extent, while fruit farms suffer losses. Altogether, the Israeli vegetative agricultural sector is expected to enjoy an increase in its accounting profits by about 7%. Surpluses of local consumers are projected to decline moderately, particularly due to the increase in fruit prices. Thus, the overall expected welfare-change is positive. This result prevails under both future climate periods and the four RCPs, with the largest (lowest) change under RPC8.5 (RCP2.6).

We turn to study trade-policy implications. According to OECD (2014), the PSE (Producer Support Estimate) measure for Israel indicates that the overall support to farmers is lower than in the average OECD country, but the fraction of trade-distorting support policies, particularly the MPS (Market Price Support), is considerably larger; hence, compliance with the WTO (World Trade Organization) rules requires removing import tariffs. This policy is examined in Scenario 2, where we simulate abolishment of tariffs such that import prices of all vegetative agricultural products equal their world-price counterparts, as forecasted based on Eboli et al. (2010). Table 8 reports the simulated climate-change effects on the welfare measures under the free trade scenario.

Table 8 about here

To comprehend the impact of the free-trade policy, compare Table 8 with Table 7. The accounting profits of vegetable and field-crop growers slightly increase under the free trade scenario, whereas fruit growers face a considerable drop in profits, particularly because imports of fruits climb to more than 50% of local consumption compared to merely 20% under the prevailing constrained-trade regime (Scenario 1). Consumer surpluses associated with vegetables rise more than under the current trade barriers, while the surplus associated with fruits drops much more moderately. Figure 2 summarizes the effect of the removal of import tariffs by depicting the difference it makes to the accounting profit, consumer surplus and social welfare (i.e., the values in Table 8 minus their counterparts in Table 7). In general, under the relatively large climate-change scenarios, which are driven by large CO_2 concentrations (i.e., RCP 8.5 in 2040-2060 and RCPs 4.5, 6 and 8.5 in 2060-2080), the benefits to consumers from removing the import tariffs exceed the losses to producers such that social welfare increases.

Figure 2 about here

In Scenarios 3 and 4 we isolate the effects of changes in precipitation and temperature, respectively. To this end, we rerun Scenario 1 while changing only one of the two climate variables. This exercise (Table 9) reveals that the aforementioned climate-change-driven welfare benefits stem from the considerable rise in temperature, as forecasted by all GCMs (Table 2). The precipitation changes lead in most cases to welfare losses that are much smaller in magnitude than the welfare benefits of the temperature changes.[15]

Table 9 about here

Under each of the latter four scenarios, farmers adapt to the changes in climate conditions by reallocating their land across the three crop bundles. In Scenario 5, we assume that farmers also adapt by offsetting the change in precipitation by applying additional irrigation water. This scenario is equivalent to Scenario 4, except that the input-price index varies according to the costs associated with changing the irrigation so as to compensate for the change in precipitation. The share of irrigation costs in the total explicit costs of each crop in each bundle (α_n^{kj} in Eq. (14)) is computed using cost-and-return studies (IMARD).[16] Note that increasing irrigation implies higher agricultural water consumption, which is possible if water quotas are not binding, or otherwise they should be extended; as aforementioned, we find water quotas ineffective, and assume that this is also the case under the simulated change. Scenario 5 (Table 9), compared to Scenario 1 (Table 7), shows that offsetting the precipitation changes by increasing irrigation is socially unbeneficial. Nevertheless, from the farmers' point of view, this adaptation strategy is warranted.

Our last issue is the role played by land reallocation in the adaptation to the projected climate changes. In this case, rather than the accounting profit, the economic profit ($\sum_{i=1}^{I}\sum_{j=1}^{J} s_{jit}^{*}\left(\mathbf{z}_{it}\right)\mathbf{V}_{j}\mathbf{z}_{jit}$) is the appropriate measure, as it dictates land-use adaptation. Based on comparison to the economic profits without land responses ($\sum_{i=1}^{I}\sum_{j=1}^{J} s_{ji1}\mathbf{V}_{j}\mathbf{z}_{jit}$), we attribute about 18% of the overall profit increase due to climate change ($\sum_{i=1}^{I}\sum_{j=1}^{J} s_{jit}^{*}\left(\mathbf{z}_{it}\right)\mathbf{V}_{j}\mathbf{z}_{jit} - \sum_{i=1}^{I}\sum_{j=1}^{J} s_{ji1}^{*}\left(\mathbf{z}_{i1}\right)\mathbf{V}_{j}\mathbf{z}_{ji1}$), to land adaptation.[17]

Concluding Remarks

This paper develops an integrated micro-macro structural econometric framework for assessing climate-change impacts on vegetative agricultural production under equilibrium in the food markets. The linkage between micro and macro levels is particularly important as governments and international organizations alike are called upon to revise current policies in order to provide 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). Taking food prices into consideration is extremely important given their relevance to the critical issues of poverty, food security and malnutrition around the world. Indeed, our empirical analysis for the case of Israel shows different simulation results when import tariffs are abolished compared with the more realistic case of restricted trade.

Agricultural adaptation to climate change calls for government interventions because of equity concerns and prioritization (e.g., Lobell et al. 2008). Impacts of some interventions can be directly identified from the results of this paper. The results also indicate directions for further research and extensions. 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 adversely affected whereas producers benefit from the projected future climate conditions. 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 technological channels through which projected consumer and producer surpluses change 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 the surpluses of both producers and consumers of fruits in Israel are projected to decline, whereas the surpluses associated with vegetables are projected to increase for both producers and consumers. Hence, proactive adaptation efforts should be directed toward fruits. Likewise, specific technology components of the agricultural systems could also be targeted, as done by 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 values through agricultural productivity adjustments and land-use adaptation (e.g., Kan et al., 2008) could also be assessed (e.g., Bateman et al. 2013). This would also require a refinement of the econometric model to enable estimation of intra-growing season input applications and environmental effects such as polluting effluents. In turn, this could alter the conclusions about the efficiency and equity of agricultural policies and public investments targeted at climate-change adaptation, since total climate-driven effects on overall social welfare may significantly differ from the effects on private consumers and producer surpluses. For instance, the projected conversion of land planted with fruit orchards and vegetables into land used for field-crop production is presumably coming along with benefits in agricultural amenities such as landscape and recreational services (open fields versus greenhouses and protected crops) as well as changes in the use of polluting inputs and irrigation water.

Finally, as aforementioned, the model can be linked to input-supply models through the cost variables. For example, integrating the agricultural supply model into a hydro-economic model (e.g., Reznik et al., 2017) would enable considering water prices endogenously. Moreover, applying the model in conjunction with more sophisticated macro models such as CGE 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 other agricultural protection policies such as 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	608	0.000	0.000	0.830	0.170
Field crops	44	0.000	0.963	0.000	0.037
Field crops & Fruits	1,173	0.000	0.606	0.343	0.050
Vegetables	53	0.800	0.000	0.000	0.200
Vegetables & Fruits	817	0.319	0.000	0.543	0.138
Vegetables & Field crops	158	0.182	0.794	0.000	0.024
Vegetables & Field crops & Fruits	4,716	0.181	0.532	0.241	0.046
Total	7,569	0.150	0.547	0.260	0.043

a. Weighted by communities' total agricultural land.

Table 2 - Descriptive statistics of the explanatory variables

Variable	Units	Mean	Std.
Production (x)			
Precipitation	mm/year	449.8	87.83
Temperature	C^{o}	19.29	0.546
Moshav	dummy	0.544	0.498
Private community	dummy	0.094	0.292
Light soil	dummy	0.566	0.496
Output price indices (ρ_j)			
Vegetables price index	index	0.526	0.068
Field-crops price index	index	0.663	0.081
Fruits price index	index	0.654	0.127
Costs (w)			
Distance to Tel-Aviv	km	71.79	41.45
Water quota	$10^6 \times m^3$/year	1.393	0.949
Agricultural land	$10^3 \times m^2$	6,217	5,963
Vegetables inputs price index	index	0.522	0.107
Field-crops inputs price index	index	0.489	0.100
Fruits inputs price index	index	1.654	0.338

Table 3 – Future forecasts of state-wide average climate variables

Climate Period	RCP	Climate Model	Precipitation (mm/year)	Temperature (C°)
Base			450	19
2040-2060	2.6	CCSM4	463	22
		MIROC5	424	23
		NorESM1	464	23
		Average	450	23
	4.5	CCSM4	443	23
		MIROC5	439	24
		NorESM1	387	23
		Average	423	23
	6	CCSM4	428	23
		MIROC5	433	23
		NorESM1	500	23
		Average	454	23
	8.5	CCSM4	381	24
		MIROC5	406	24
		NorESM1	395	24
		Average	394	24
	Average		430	23
2060-2080	2.6	CCSM4	423	23
		MIROC5	426	23
		NorESM1	397	23
		Average	415	23
	4.5	CCSM4	421	23
		MIROC5	398	25
		NorESM1	336	23
		Average	385	24
	6	CCSM4	401	24
		MIROC5	399	24
		NorESM1	381	23
		Average	393	24
	8.5	CCSM4	367	25
		MIROC5	360	25
		NorESM1	334	25
		Average	353	25
	Average		387	24

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

Log likelihood	-7657.6		
Wald $\chi^2(91)$	29144.1		
Variable	**Vegetables**	**Field crops**	**Fruits**
Production			
$\rho_j \times$ Precipitation	0.008**	0.002	0.008***
$\rho_j \times$ Precipitation^2	-1.53×10^{-5}***	1.17×10^{-6}	-4.96×10^{-6}*
$\rho_j \times$ Temperature	-4.615**	-0.622	-0.557
$\rho_j \times$ Temperature^2	0.125**	0.027	0.015
$\rho_j \times$ Moshav	-2.019***	-2.917***	-1.032***
$\rho_j \times$ Light soil	-0.661***	-0.511***	0.171***
ρ_j	47.683**	3.310	5.831
Costs			
Distance to Tel-Aviv	-0.006***	-0.011***	0.005***
Water quota	0.546***	0.441***	0.105
Water-quota^2	-0.147***	-0.113***	-0.103***
Agricultural land	0.096***	0.132***	0.090***
Agricultural-land^2	-0.002***	-0.002***	-0.002***
Inputs price index	-1.750***	0.780***	-1.547***
Constant	-0.293	1.370***	0.604***

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

a. Coefficients for Ecological Regions are not reported. The dummy variable for private communities was omitted due to collinearity.

Table 5 - Marginal effects

	Land share				Economic Profit			
Variable	**Vegetables**	**Field crops**	**Fruits**	**Total cultivated**	**Vegetables**	**Field crops**	**Fruits**	**Total**
Production								
Precipitation	-0.001***	3.23×10^{-4}***	4.35×10^{-4}***	6.46×10^{-5}**	-0.001***	0.002***	0.002***	0.002***
Temperature	-0.007	0.062***	-0.047***	0.008**	0.009	0.260***	-0.084**	0.185***
Moshav	0.033***	-0.294***	0.192***	-0.069***	-0.131***	-1.499***	0.118***	-1.512***
Light Soil	-0.027***	-0.076***	0.093***	-0.010***	-0.082***	-0.314***	0.204***	-0.191***
Vegetables price index (ρ_v)	0.455***	-0.245***	-0.179***	0.03***	1.005***	-0.515***	-0.321***	0.168***
Field-crops price index (ρ_f)	-0.020***	0.068***	-0.042***	0.007***	-0.020***	0.269***	-0.075***	0.174***
Fruits price index (ρ_p)	-0.102***	-0.300***	0.439***	0.037***	-0.105***	-0.631***	1.445***	0.709***
Costs								
Distance to Tel-Aviv	-3.3×10^{-4}	-0.003***	0.003***	-2.3×10^{-4}***	-0.001***	-0.011***	0.007***	-0.005***
Water quota	0.002***	0.005***	-0.007***	-1.06×10^{-4}	0.004***	0.016***	-0.018***	0.002
Agricultural land	-0.001	0.011***	-0.005***	0.004***	0.010***	0.069***	0.013***	0.093***
Inputs price index	-0.205***	0.552***	-0.372***	-0.024*	-0.482***	1.517***	-1.181***	-0.147

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

Table 6 – Climate-change impact on partial-equilibrium indices under constrained-trade policy (Scenario 1)

		Price Index (ϕ_{jt}^{p})			Demand Quantity Index (ϕ_{jt}^{q})			Supply Quantity Index (ϕ_{jt}^{y})			Land Share Index (s_{jt}/s_{j1})		
Climate Period	RCP	Vegetables	Field Crops	Fruits	Vegetables	Field Crops[a]	Fruits	Vegetables	Field Crops	Fruits	Vegetables	Field Crops	Fruits
2040-2060	2.6	0.877	1.033	1.259	1.164	0.997	0.755	1.163	2.258	0.682	0.946	1.079	0.846
	4.5	0.822	1.033	1.259	1.254	0.997	0.755	1.253	2.387	0.603	0.941	1.088	0.826
	6.0	0.868	1.033	1.259	1.178	0.997	0.755	1.177	2.368	0.659	0.943	1.084	0.836
	8.5	0.733	1.033	1.259	1.435	0.997	0.755	1.433	2.750	0.489	0.931	1.106	0.790
	Average	0.825	1.033	1.259	1.258	0.997	0.755	1.257	2.441	0.608	0.940	1.089	0.824
2060-2080	2.6	0.837	1.057	1.281	1.226	0.995	0.742	1.225	2.258	0.609	0.944	1.084	0.835
	4.5	0.740	1.057	1.281	1.429	0.995	0.742	1.427	2.708	0.480	0.932	1.105	0.792
	6.0	0.755	1.057	1.281	1.386	0.995	0.742	1.385	2.632	0.502	0.933	1.102	0.798
	8.5	0.634	1.057	1.281	1.728	0.995	0.742	1.726	3.313	0.353	0.918	1.127	0.747
	Average	0.741	1.057	1.281	1.442	0.995	0.742	1.441	2.728	0.486	0.932	1.104	0.793

Table 7 – Climate-change impact on aggregate welfare measures under restricted-trade policy (Scenario 1), (10^6 \$/year)

		Accounting Profit[a]				Consumer Surplus				Social Welfare			
Climate Period	**RCP**	**Vegetables**	**Field Crops**	**Fruits**	**Total**	**Vegetables**	**Field Crops**	**Fruits**	**Total**	**Vegetables**	**Field Crops**	**Fruits**	**Total**
2040-2060	2.6	36	253	-61	228	70	-26	-145	-101	107	228	-207	128
	4.5	44	279	-121	201	105	-26	-145	-66	150	253	-267	135
	6.0	39	275	-78	236	76	-26	-145	-95	115	249	-224	141
	8.5	62	350	-208	204	167	-26	-145	-3	230	325	-354	200
	Average	45	289	-117	217	105	-26	-145	-66	150	264	-263	151
2060-2080	2.6	41	263	-110	194	95	-44	-156	-105	136	219	-266	89
	4.5	61	354	-209	206	164	-44	-156	-36	225	310	-365	170
	6.0	57	339	-192	204	152	-44	-156	-48	209	295	-349	155
	8.5	90	477	-306	261	251	-44	-156	50	341	433	-463	312
	Average	62	359	-204	217	166	-44	-156	-34	228	314	-361	182

a. Accounting profits at the base period amount to \$119, \$656, \$2,146 and \$2,921 million/year for vegetables, field crops, fruits and overall, respectively.

Table 8 – Climate-change impact on aggregate welfare measures under abolishment of import tariffs (Scenario 2), (10^6 \$/year)

		Accounting Profit				Consumer Surplus				Social Welfare			
Climate Period	RCP	Vegetables	Field Crops	Fruits	Total	Vegetables	Field Crops	Fruits	Total	Vegetables	Field Crops	Fruits	Total
2040-2060	2.6	40	266	-250	57	77	-26	-15	36	117	240	-265	93
	4.5	48	291	-289	49	112	-26	-15	71	160	265	-304	120
	6.0	43	288	-263	68	82	-26	-15	41	125	262	-277	110
	8.5	66	361	-346	82	174	-26	-15	133	239	336	-361	214
	Average	49	302	-287	64	111	-26	-15	70	160	276	-302	134
2060-2080	2.6	45	275	-281	39	102	-44	-26	32	147	231	-307	71
	4.5	65	365	-346	85	170	-44	-26	99	235	321	-372	184
	6.0	61	350	-335	77	158	-44	-26	87	219	306	-361	164
	8.5	94	487	-409	172	256	-44	-26	186	350	443	-435	358
	Average	66	370	-343	93	171	-44	-26	101	238	325	-369	194

Table 9 - Impacts on welfare measures of changes in precipitation only (Scenario 3), temperature only (Scenario 4), and offsetting precipitation change by irrigation (Scenario 5) (10^6 \$/year)

		Scenario 3 Change in Precipitation Only			Scenario 4 Change in Temperature Only			Scenario 5 Offsetting Precipitation Change by Irrigation		
Climate Period	RCP	Accounting Profit	Consumer Surplus	Social Welfare	Accounting Profit	Consumer Surplus	Social Welfare	Accounting Profit	Consumer Surplus	Social Welfare
2040-2060	2.6	10	-11	-1	218	-106	112	222	-104	118
	4.5	-5	-13	-17	229	-88	141	212	-96	115
	6.0	12	-11	1	223	-96	127	230	-92	138
	8.5	-21	-19	-40	266	-43	223	227	-63	164
	Average	-1	-13	-14	234	-83	151	223	-89	134
2060-2080	2.6	-4	-35	-39	238	-134	104	214	-146	68
	4.5	-20	-48	-68	284	-81	204	239	-104	135
	6.0	-16	-40	-56	271	-90	181	232	-110	122
	8.5	-37	-60	-97	358	-11	347	292	-46	246
	Average	-19	-45	-65	288	-79	209	244	-102	143

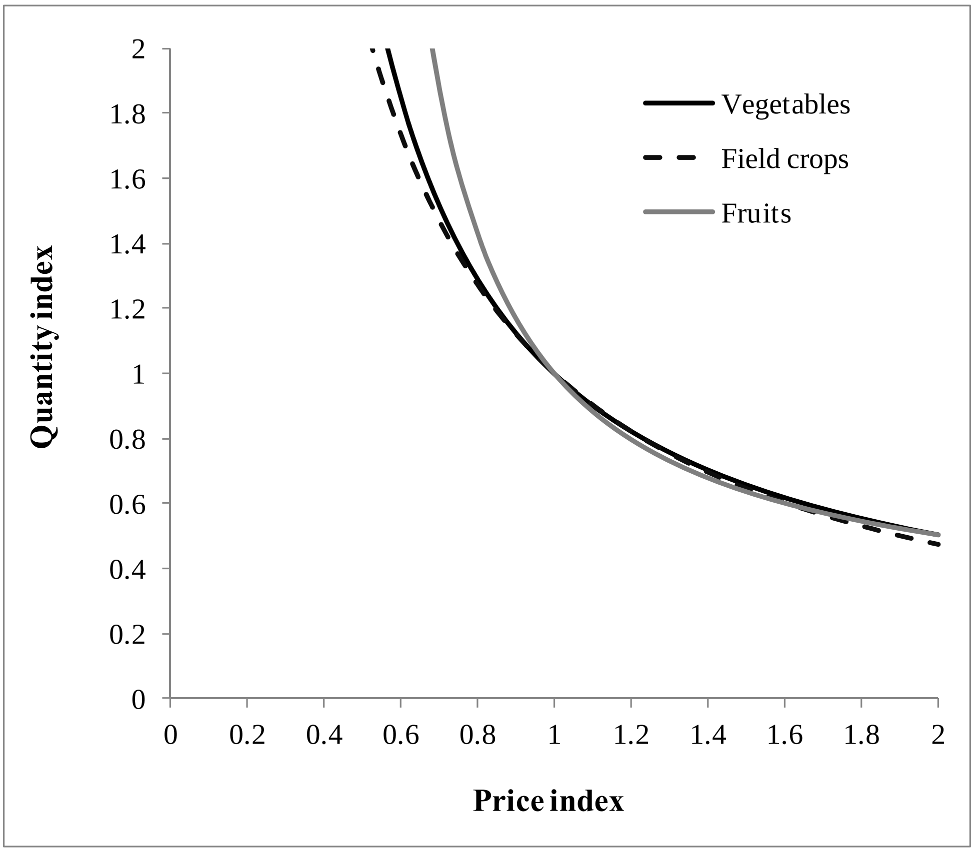

Figure 1 - Demand curves of the three crop bundles

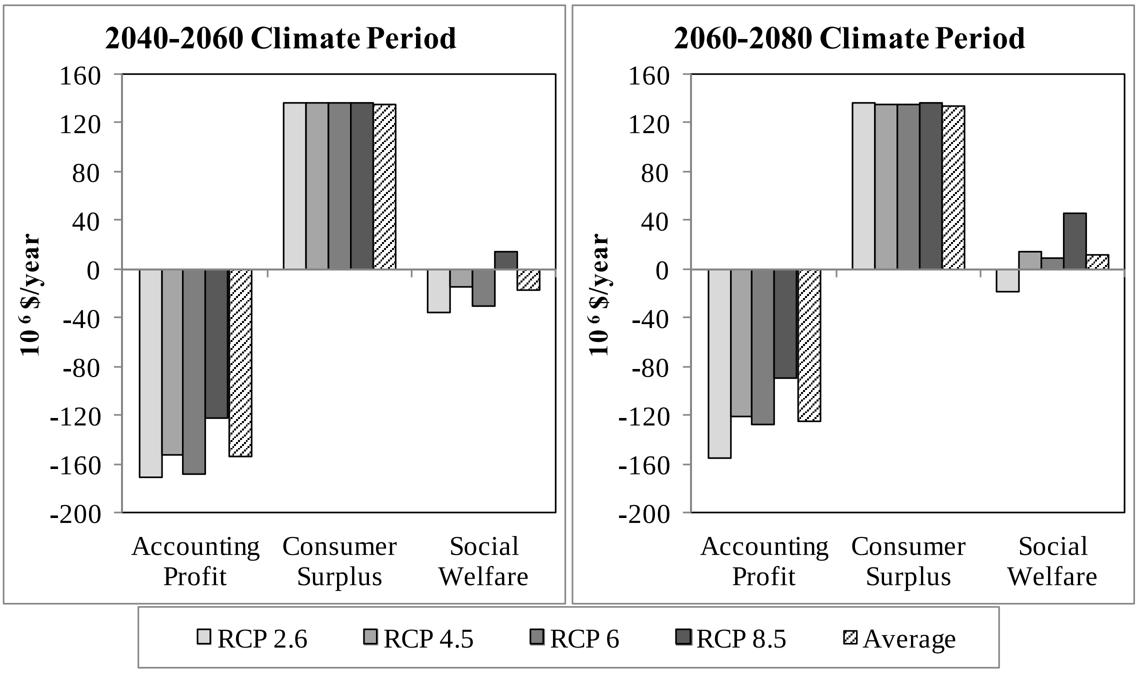

Figure 2 – Difference in welfare elements between the free- and restricted-trade scenarios (free-trade (Table 8) minus restricted trade (Table7)).

Appendix A – Derivation of the optimal land-share in Eq. (3)

The farmer's problem is (we omit the farm index for notation brevity):

$$\max_{\mathbf{s}} \Pi = \sum_{j=1}^{J} s_j \mathbf{v}_j \mathbf{z}_j - \frac{1}{a} \sum_{j=1}^{J} s_j \ln\left(s_j\right) \quad s.t. \quad \sum_{j=1}^{J} s_j \leq 1 \tag{A1}$$

Using the FOC

$$\frac{\partial \Pi}{\partial s_j} = \mathbf{v}_j \mathbf{z}_j - \frac{1}{a}\left(\ln\left(s_j\right)+1\right) - \lambda = 0 \tag{A2}$$

we get the land share:

$$s_j = \frac{\exp\left(a\left(\mathbf{v}_j \mathbf{z}_j\right)\right)}{\exp\left(a\lambda+1\right)} \tag{A3}$$

Substituting Eq. (A3) into the land constraint in (A1),

$$\sum_{j=1}^{J} s_j = \exp\left(-a\lambda-1\right) \sum_{j=1}^{J} \exp\left(a\left(\mathbf{v}_j \mathbf{z}_j\right)\right) = 1 \tag{A4}$$

we get the shadow value

$$\lambda = \frac{\ln\left[\sum_{j=1}^{J} \exp\left(a\left(\mathbf{v}_j \mathbf{z}_j\right)\right)\right] - 1}{a} \tag{A5}$$

which we substitute back into the land share in Eq. (A3) to get Eq. (4).

Appendix B – Nationwide data at the base year for the crops in the three crop bundles

Crop	Land (L^{kj}, hectares)	Quantity (Q_1^{kj}, ton/year)	Price (p_1^{kj}, $/ton)	Demand Elasticity (β^{kj})	Explicit cost (C^{kj}, $/hectare)	Import tariff (% of world price)
Vegetables						
Watermelon	15,461	184,596	216	-0.7	8,917	29
Melon	2,888	48,993	654	-0.7	2,004	47
Tomato	4,291	288,621	1,178	-0.7	23,320	42
Strawberry	454	9,614	2,493	-0.7	66,511	35
Potato	12,742	196,680	461	-2.2	10,060	78
Cucumber	1,827	67,870	536	-0.3	35,211	12
Eggplant	798	28,517	423	-0.3	6,994	20
Pepper	2,475	50,946	818	-1.3	21,586	32
Zucchini	971	17,968	560	-1.1	2,059	17
Onion	3,210	53,860	313	-1.1	8,811	61
Carrot	1,265	50,938	332	-1.5	24,443	58
Lettuce	1,262	22,441	540	-1.1	26,771	10
Cabbage	1,980	37,082	292	-1.1	15,029	39
Cauliflower	1,579	18,177	413	-1.1	12,813	29
Celery	521	10,606	551	-1.3	5,357	19
Radish	415	7,243	421	-1.1	5,384	111
Field crops – local						
Cotton, raw	11,646	92,668	991	-	2,663	0
Chickpea	7,558	9,328	998	-	296	0
Corn	5,233	98,766	358	-	3,215	0
Pea	2,162	8,945	626	-	597	0
Peanuts	3,744	24,169	1,592	-	1,196	0
Sunflowers	7,680	19,447	1,340	-	994	0
Wheat	83,646	160,260	260	-	74	0
Barley	8,364	5,342	257	-	60	0
Hay	64,294	86,188	146	-	73	0
Field crops - import						
Cotton, lint	-	12,381	16,213	-0.06	-	-
Chickpea	-	8,000	998	-0.7	-	-
Corn	-	796,836	358	-1.6	-	-
Pea	-	2,400	626	-1.5	-	-
Peanuts	-	2,901	1,592	-0.3	-	-

Wheat	-	1,582,069	260	-2.0	-	-
Barley	-	233,808	257	-0.85	-	-
Fruits						
Apple	5,506	119,316	987	-1.9	6,186	39
Pear	1,676	25,055	1,190	-1.3	4,274	39
Peach	5,630	51,298	1,177	-0.7	7,839	21
Grapes	11,740	95,295	923	-1.0	5,959	31
Banana	2,382	94,590	762	-1.5	6,456	37
Avocado	5,709	69,157	1,180	-3.8	2,082	40
Dates	3,441	12,276	3,297	-5.3	6,640	48
Orange	3,303	376,476	377	-0.4	1,277	5
Grapefruit	7,763	520,864	343	-0.2	2,332	24
Lemon	1,726	45,122	432	-1.4	2,696	27
Olive	20,034	34,450	1,262	-1.7	1,664	49
Almond	2,979	4,086	2,110	-1.7	1,074	9

Notes

1 While the linear function is adopted to facilitate the analysis, the model can be easily extended; for example, Kaminski et al. (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.

2 The resultant linear equations are of the form $\ln\left(s_{ji}^{*} / s_{Ji}^{*}\right) = \mathbf{V}_j \mathbf{z}_{ji} + u_{ji}$, where u_{ji} is an error term.

3 In case that only regional data are available one may overcome endogeneity by employing 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.

4 Kaminski et al. (2013) show that, to enable identification of the parameters $\mathbf{v}_j$ for $j = 1,\ldots, J-1$, a can be calibrated by the use of panel data and additional information on crop profitability.

5 We employ this assumption to derive bundle-level quantity indices, since disaggregated land-use data are usually available only for bundles of crops, whereas aggregated quantities and prices may be available for the various crops in each bundle.

6 According to Finkelshtain and Kachel (2009), 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 world prices under equilibrium, our analysis is limited to the case of Israel's local market under partial equilibrium.

[7] Data is not available for later years due to changes in the data collection procedure.

[8] The number of lags was determined after ARIMA estimations using R^2 and Akaike-Schwartz information criteria.

[9] For consistency with the estimated coefficients $\mathbf{V}_j = \left(a\mathbf{b}_j, -a\left(\boldsymbol{\gamma}_j - \boldsymbol{\gamma}_J\right)\right)$, 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.

[10] The allocation of products between the local and international markets frequently occurs at the wholesale markets; that is, beyond the control of farmers (Kachel, Y., personal communication, May 2014).

[11] These projections represent the effect of climate change in comparison to a baseline scenario without the climate-change impact. In our case we simulate changes in climate variables and prices where all other elements of the economy are assumed to remain at their base-year levels.

[12] These regions were determined by the ICBS (2010) based on criteria such as topography, climate, demography and history. Thus, the 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.

[13] Standard errors were estimated using the bootstrap procedure.

[14] The predicted responses to temporal changes in climate variables are based on the spatial variations of these variables across communities in the sample period. Hence, the larger the spatial variability in comparison to the temporal variation, the larger the validity of the simulation predictions for changed climate conditions; in our case, the spatial variance among communities captures 96% and 69% of the total spatiotemporal variance of precipitation and temperature, respectively.

[15] Kawasaki and Uchida (2016) also found that a rise in temperature benefits farmers by increasing crop yields. However, they also found that at the same time crop quality may decline. We cannot account for this effect with our data. A number of recent articles (e.g., Salazar-Espinoza et al., 2015 and Khanal and Mishra, 2017) have focused on climate uncertainty rather than climate trends. However, Yang and Shumway (2015) have found that farmers' adjustment to climate change is not affected much by ignoring climate uncertainty.

[16] Irrigation constitutes 9%, 38% and 17% out of total explicit costs of vegetables, field crops and fruits, respectively.

[17] While this seems to be a small number, farmers could adapt in other ways in addition to land reallocation. Burke and Emerick (2016) have found that the adaptation capacity of US farmers is quite limited. However, Miao at al. (2016) have found that the price responsiveness of land allocation is larger than that of yield. Also, Trapp (2014) has found that farm-level adaptation, especially cropland expansion and crop portfolio adjustments, can largely mitigate negative impacts of climate change on regional crop production in the EU.