Commodity Prices and Volatility in Response to Anticipated Climate Change

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Abstract

Mounting evidence indicates climate change will adversely influence agricultural crop yields and cause greater year-to-year variability. This paper considers how a rational, forward-looking and competitive commodity market would account for these anticipated changes and thereby influence time path of storage, prices, price volatility, and social welfare. We forecast 1600 hypothetical yield paths from 2000 to 2080 using estimates from a recent global statistical analysis of weather and crop yields combined with projections from 16 climate models. We then extend the dynamic competitive storage model to account for land response to price and anticipated yield shift. We simulate 1600 stochastic-equilibrium price paths under climate change relative to a baseline of stable prices using our hypothetical yield paths together with estimated demand and supply elasticities and storage cost from the literature. Our results indicate that, under the impact of climate change, world crop price level will increase twofold and world crop price volatility will increase fivefold between 2000 and 2080. Welfare analysis suggests that by 2020, the world would have welfare loss equivalent to food for 180 to 200 million people annually.

1 Introduction

Internationally traded food prices have been on the rise since 2002, especially after 2006. The FAO food price index hit its all-time high of 238 points in February 2011, passing the previous record level set in the summer of 2008. High food prices have had detrimental effects on the well-being of consumers, particularly those in less-developed areas in Asia and Africa where food expenditures can account for more than fifty percent of total household income. Rising food prices also have also caused food riots in several countries, and led to policy interventions such as grain export bans and tariff reductions in others. In this paper we consider the influence of anticipated climate change on the level and volatility of food crop prices.

Although the recent food price spikes can be attributed to several factors such as demand growth from emerging economies and the global surge of biofuels production, the role of weather anomalies in recent years is unquestionable. The high inelasticity of demand for commodity crops makes crop prices highly sensitive to yield shocks, and mounting evidence indicates that climate change will continue to adversely influence agricultural crop yields and cause greater year-to-year variability. A rational, forward-looking and competitive commodity market would account for these anticipated changes, thereby influencing the time path of storage, price level and volatility, and social welfare.

While lower crop yields positively affect price, higher yield variance will have an ambiguous impact on crop price volatility. Competitive storage plays a central role in clearing the market for food crops, and storage theory suggests that crop yield is an important factor in the formation of inventory. Positive yield shocks lead to accumulation of inventory to take advantage of low current prices relative to the price expected at some point in the future. While the current price is a direct function of current yield, future prices are uncertain and expectations are formed based on the distribution of past yield realizations. When yield variability increases, a gap between the current and expected future prices will occur with greater frequency, leading to an increase in inventory being held. Therefore, while increased year-to-year yield variability will lead to greater price fluctuations, we also have higher inventory which acts as a buffer stock, dampening the price effect of adverse shocks in the system. As a result, when crop yield variance increases, price volatility will either increase or decrease depending on other factors such as demand elasticity and storage cost.

The welfare effects are also ambiguous. Standard neoclassical theory predicts that exogenous price volatility is welfare increasing; however, with the existence of a competitive storage market, the fact that higher price volatility leads to increased inventories ultimately results in greater spoilage and loss, and thus higher overall prices.

In this paper, we combine the anticipated effects of climate change on yield levels and volatility with an empirical competitive storage model to examine how expected climate change might affect prices and social welfare in the international food commodity market. We expand on previously used storage models to allow for a supply response, and examine a dynamic case in the face of a non-stationary yield distribution. To our knowledge, this is the first study to do this. We also look at the impact of yield trend and yield volatility separately on price and welfare analysis.

We calibrate anticipated changes in crop yield distributions by forecasting from a recent global statistical analysis of weather and crop yields of four key crops (maize, rice, soybeans and wheat), using projections from 16 climate models (Lobell, Schlenker, and Costa-Roberts (2011)). These crops represent roughly eighty percent of global calories, and their prices tend to fluctuate together suggesting that they are close substitutes in production and consumption; we convert the crop yields into edible calories and aggregate the four series into one series of global caloric yield for use in the storage model. We use stochastic dynamic programming to solve for dynamic competitive storage market equilibria for the case of a gradually changing yield distribution as forecast by the climate models, and for a baseline case assuming a stationary yield distribution. The storage function implicitly determines consumption and price as a function of the yield outcome and inventories carried over from the previous year. We feed the forecasted time paths of yields into the sequence of storage functions, and simulate time paths of price, consumption and storage outcomes, and calculate producer and consumer surplus. These time paths of prices are compared to those simulated using the stationary storage model from the baseline case.

There is some debate in the storage literature about the appropriate magnitude of the supply and demand parameters (e.g. Williams and Wright (1991), Deaton and Laroque (1996), Cafiero, Bobenrieth H., Bobenrieth H., and Wright (2011)) We perform the analysis using a range of elasticity estimates to determine the extent to which our results are affected by these parameters. While climate change is a gradual process, these results provide an indication of how expectations about climate change could influence current commodity price levels, as well as volatility over the coming decades.

We show that price level and volatility do increase over time in response to decreasing yield, and increasing yield variability. Production and consumption continue to fall leading to a decrease in consumer surplus, and a corresponding though smaller increase in producer surplus. Depending on assumptions regarding demand and supply elasticities, welfare loss can amount to enough food for 180 to 200 million people annually by the year 2020. In the next section we introduce the theoretical framework, and describe our procedure for solving the storage model.

2 Theoretical framework

Consider a competitive world food market with storable commodities, and no trade. Total harvest in period t is equal to yield times the amount of land planted in the previous period, $q_t = y_t l_{t-1}$.

Yield, y_t, is a random process partially determined by weather:

$$y_t = h(w_t) + \varepsilon_t, \tag{1}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. We examine what happens to storage behavior and price volatility when the market experiences a shift in the yield distribution, similar to what we might expect from climate change. In particular, suppose that current weather realizations are i.i.d. with mean ω, and variance σ_w^2. At time $t = 0$ climate starts to shift gradually, moving towards a new equilibrium distribution in which weather realizations have mean $\widetilde{\omega}$, and variance $\widetilde{\sigma_w^2}$. Suppose further that, along the adjustment path, weather realizations have mean $\widetilde{\omega}_t$, and variance $\widetilde{\sigma_{w_t}^2}$, and will stabilize at the new stationary distribution at time T. Then:

$$y_t \sim N(h(\widetilde{\omega}_t), h'(\widetilde{\omega}_t)^2 \widetilde{\sigma_{w_t}^2} + \sigma_\varepsilon^2) \text{ for } t = 0, \cdots, T-1,$$

and

$$\widetilde{y}_t \sim N(h(\widetilde{\omega}), h'(\widetilde{\omega})^2 \widetilde{\sigma_w^2} + \sigma_\varepsilon^2) \text{ for } t \geq T.$$

Consistent with the literature on agricultural impacts of climate change (e.g. IPCC (2007), Schlenker and Roberts (2009), Schlenker and Lobell (2010)), we assume that $h(\widetilde{\omega}) < h(\omega)$, and $\widetilde{\sigma_w^2} > \sigma_w^2$. We also assume that $h(\cdot)$ remains unchanged, and that σ_ε^2 is a constant proportion of the total variance[1].

The market is characterized by land choice as an increasing function of expected future price:

$$l_t = G(E_t(p_{t+1})); \tag{2}$$

and an inverse demand function for food:

$$p_t = F(q_t). \tag{3}$$

[1]This is unrealistic, but combined with the other assumptions inherent in the model (e.g. constant demand) is equivalent to the assumption that all other changes (e.g. technological change, population growth) balance each other out.

In the event of a positive yield shock, the current price will be low relative to the expected future price, providing an opportunity to profit from storage. Let z_t denote the amount of food on hand at the beginning of the period; this will equal storage from the last period, x_{t-1}, minus depreciation, plus the new harvest q_t:

$$\begin{aligned} z_t &= q_t + (1-d)x_{t-1} \\ &= c_t + x_t, \end{aligned} \tag{4}$$

where d is the rate of decay in storage, and c_t is consumption this period. Assume storage cost is an increasing function of the food stored:

$$K(x_t) = k_0 x_t + \frac{1}{2} k_1 x_t^2,$$

with $k_0 > 0$ and $k_1 \geq 0$.[2] Then the arbitrage conditions for the competitive storage market are:

$$\left\{ \begin{array}{c} p_t + k_0 + k_1 x_t = \frac{1-d}{1+r} E_t(p_{t+1}), \text{ when } x_t > 0; \\ p_t + k_0 + k_1 x_t \geq \frac{1-d}{1+r} E_t(p_{t+1}), \text{ when } x_t = 0 \end{array} \right\}, \tag{5}$$

where r is the interest rate.

One of the key features of the storage model described by (5) is the non-negativity of storage. When there is no storage, all of the amount on hand this period will be consumed; the inverse demand function will be a function of the amount on hand:

$$p_t = F(z_t). \tag{6}$$

In the case of storage, consumption is less than the amount on hand; current price therefore, is greater than $F(z_t)$ and is a function of the discounted expected future price. By combining (5)

[2] The concept of convenience yield is not considered in this paper.

with Equation (??), we can express price as:

$$p_t = max\left\{\beta E_t(p_{t+1}) - k_0 - k_1 x_t, F(z_t)\right\}, \tag{7}$$

where $\beta = \frac{1-d}{1+r}$.

Given the assumptions of costly storage, and i.i.d. harvests, others have established the existence of a stationary rational expectations equilibrium (SREE) (e.g. Deaton and Laroque (1992)). Using this framework, it is relatively straightforward to analyze the comparative statics of two separate, stationary yield distributions like those described above. In the absence of storage, this shift in the yield distribution would lead to an unambiguous increase in price volatility. However, we can see from the arbitrage conditions in (5) that storage acts to dampen price spikes. In the presence of storage (i.e. $x > 0$), the current price plus marginal storage cost cannot exceed the discounted expected future price. If it did, storers would store less, increasing the supply available to consumers and thus decreasing the current price until it was exactly equal to the discounted expected future price minus the marginal storage cost. Similarly, the discounted expected future price will not exceed the current price by more than the marginal storage cost. If it did, storers would act to maximize expected profit by increasing current storage, thus driving up the current price until the wedge between the current price and the discounted expected future price were equal to the marginal storage cost. The expected decrease in average yields increases the expected future price, and increased yield variability increases the probably of observing a gap between the expected future price and the current price, both of which lead to increased storage. Therefore, while our model predicts an unambiguous increase in storage, the effect on price volatility is ambiguous and needs to be analyzed empirically.

One problem with comparing the two stationary cases described above is that climate change is a slow process, and any meaningful differences in the distribution of yields would take decades to observe. Discussing projected price fluctuations for a date so far into the future would not be a worthwhile exercise. However, as we will demonstrate, the intertemporal dependence in the storage model is such that expected changes in the yield distribution in the future could be reflected in the level and volatility of prices now. In this paper, rather than focus comparing the two stationary cases, we focus instead on the dynamic case along the adjustment path where harvests are not necessarily identically distributed over time. First, we need to make clear the solution of the stationary case.

2.1 Solving the stationary storage model

A rational expectations equilibrium solution in the case of a stationary yield distribution consists of a stationary price function; a mapping from all possible realizations of the state variable z to a corresponding equilibrium price p. However, even if the functional forms of $F(\cdot)$ and $G(\cdot)$ are known, an analytical solution is not possible. The solution is complicated by the fact that the current storage decision depends on the current stock (which depends on past storage), in addition to both current and expected future prices (which in turn depend on current and future storage, respectively.) Calculating a solution for equilibrium in the storage model requires the use of stochastic dynamic programming. We can also see that the market demand function will not be smooth. When z_t is sufficiently low, all available supply is consumed, and p_t high relative to $E(p_{t+1})$. However, as z_t increases, p_t eventually decreases sufficiently as to make storage profitable. At this point, the "stockout" price, there is a kink in the market demand function. Therefore, the solution involves the use of a flexible functional form to approximate the control variable price p as a function of the amount on hand z. We extend the previous literature by adjusting the numerical procedure to allow for supply response in the storage model, and in the next section we extend it further to account for the non-stationary scenario.

Assume that the inverse consumption demand, and the land supply response functions have the following forms:

$$p_t = F(c_t) = \alpha_d + \gamma_d c_t, \tag{8}$$

$$l_t = \alpha_s + \gamma_s E_t(p_{t+1}); \tag{9}$$

with $\gamma_d < 0$ and $\gamma_s > 0$. We can rewrite Equation (7) as:

$$\begin{aligned} p_t(z_t) &= max\left\{\beta E_t(p_{t+1}(z_{t+1}) - k_0 - k_1 x_t, F(z_t)\right\} \\ &= max\left\{\beta E_t(p_{t+1}(y_{t+1} l_t + (1-d)x_t) - k_0 - k_1 x_t, F(z_t)\right\}, \end{aligned} \tag{10}$$

and from Equation (4) we have:

$$\begin{aligned} x_t &= z_t - c_t \\ &= z_t - F^{-1}(p_t(z_t)). \end{aligned} \tag{11}$$

The expected future price in this model requires integration over all values of the random yield values y_{t+1}. We initially follow the numerical method for a stationary setting, introduced by Gustafson (1958), and adapted by Deaton and Laroque (1995, 1996, 1992), and Cafiero et al. (2011). The yield distribution is discretized into N points, each with a corresponding probability $Pr(y^n_{t+1}) = Pr(y_{t+1} = y^n_{t+1})$. Thus, we rewrite Equations (7) and (9) as:

$$p_t(z_t) = max\left\{\beta \sum_{n=1}^{N} p_{t+1}(y^n_{t+1} l_t + (1-d)x_t) \times Pr(y^n_{t+1}) - k_0 - k_1 x_t, F(z_t)\right\}, \tag{12}$$

and

$$l_t = \alpha_s + \beta_s(\sum_{n=1}^{N} p_{t+1}(y^n_{t+1} l_t + (1-d)x_t) \times Pr(y^n_{t+1})), \tag{13}$$

where $\sum_{n=1}^{N} Pr(y^n_{t+1}) = 1$. Solving Equation (12) for price as a function of amount on hand, $p(z)$, is an iterative process as follows:

1. Set a range of amount on hand values $[\underline{z},\ \overline{z}]$.[3]

2. Choose the initial parameters for $F(c_t)$ and $G(E(p_{t+1}))$, and guess a set of initial values for (12), using a cubic spline over a number of possible points of the value of $z_t \in [\underline{z},\ \overline{z}]$.[4]

[3]The z_t are bounded by $[\underline{q_t}, \infty]$ where $\underline{q_t}$ is the lowest harvest possible in the model. While $\underline{z}$ can be set to zero, $\overline{z}$ needs to be carefully chosen to be greater than the highest possible amount on hand.

[4]While a higher number of points would yield a more accurate approximation of the price function, it is computa-

3. Given these initial values, calculate storage x using equation (11).

4. Using x from the previous step, solve the system of non-linear equations (13) to find the corresponding land area.

5. Compute price p using the right hand side of equation (12).

6. If the price from step 5 is equal to that in step 2, stop the iteration process. Otherwise, repeat steps 3-5, using the values generated in step 5. Repeat until prices from step 2 and 5 are equal to each other.

Now that we have a solution for the stationary case, we are prepared to examine the non-stationary case.

2.2 Solving the non-stationary storage model

Storage theory suggests that when a shock is anticipated in the system, price and storage will move together at the same direction. With an anticipated contraction in supply, storers – motivated by intertemporal arbitrage conditions – will accumulate more inventory. By doing so, they restrict the quantity of supply currently available, thus driving up current price. Normally this increase in the current price would put a hold on storers' incentive to transfer goods to the next period. Yet, because the future price is expected to keep increasing in response to the contraction in supply, more and more goods are withheld from the market which lead to increasingly higher prices during the transition period. The accumulation of storage will only cease when the total amount on hand, which equals to storage plus production, exceeds the new level of demand on hand in the new environment. From that point, price increases along the adjustment path will gradually become smaller.

We apply backward induction to the numerical methods described above, to solve the non-stationary storage model and examine how price and other variables of the model will adjust to

tionally costly. Cafiero et al. (2011) use 1000 equally spaced points so that they can find a more precise measurement of the cut-off price. We instead use 50 unequally-spaced points, with the majority of the points clustered around the no-storage equilibrium (the point where $p_t = \alpha_d + \gamma_d q_t$). We find no significant difference in the cut-off price using a finer grid of 1000 equally spaced points, and our method of 50 unequally spaced points.

an anticipated, gradual, and long-term shift in the yield distribution, such as that due to expected climate change. We first the method described above to solve for a terminal condition – the storage equilibrium in from year T on, assuming that the market equilibrium stays stationary after that. We then proceed backwards, first solving the storage model from period $T-1$, proceeding backwards one period at a time, back to period 0, the first period in which the market reacts to the news of a shift. The storage amount in period $T-1$ is:

$$\begin{aligned} x_{T-1} &= z_{T-1} - c_{T-1} \\ &= z_{T-1} - F^{-1}(p_{T-1}(z_{T-1})). \end{aligned} \tag{14}$$

We modify Equation (12) to express the relationship between $p_T(z_T)$ and $p_{T-1}(z_{T-1})$ over the range of z:

$$p_{T-1}(z_{T-1}) = max\left\{\beta\sum_{n=1}^{N} p_T(y_T^n l_{T-1} + (1-d)x_{T-1}) \times Pr(y_T^n) - k_0 - k_1 x_{T-1}, F(z_{T-1})\right\}. \tag{15}$$

We can see from Equations (14) and (15) that the storage demand function in period $T-1$ can be found once we know $p_T(z_T)$ and l_{T-1}. Recall that the land function can be implicitly solved using the following equation:

$$l_{T-1} = \alpha_s + \beta_s(\sum_{n=1}^{N} p_{T-1}(y^n l_{T-1} + (1-d)x_{T-1}) \times Pr(y^n)), \tag{16}$$

Again we use an iterative approach to find $p_{T-1}(z_{T-1})$:

1. Pick l_T as the starting values for land. (Note: we already have this from solving the stationary case above.)

2. Solve for $p_{T-1}(z_{T-1})$ using equation (15) and l_T.

3. Solve for inventory and land using equations (14) and (16).

4. If the land value replicates itself, stop and use it to solve for $p_{T-1}(z_{T-1})$. Otherwise, repeat

steps 2-4, using this new land value.

Once we have $p_{T-1}(z_{T-1})$, we use it to find $p_{T-2}(z_{T-2})$ and so on until we get to $p_0(z_0)$. In the end, we have a system of equations describing how the time paths of storage behavior and prices would reflect the market reaction to news of a gradually shifting yield distribution.

3 Estimation

Our yield data are generated using the yield response functions for corn, rice, soy, and wheat estimated in Lobell et al. (2011). They estimate historic yield shocks (from a quadratic time trend) as a quadratic function of temperature and precipitation, using a grouped bootstrap procedure to estimate the parameter distributions. We combine the first 100 bootstrap replications for each of the four crops with 120 years (1961-2080) of weather output from 16 GCMs, thus constructing 1,600 hypothetical 120-year time-series for each crop.[5] Using the conversion factors from Williamson and Williamson (1942), we convert the yield values to calories and aggregate them to obtain global caloric yield (we express this in units of number of persons fed for a year per one hectare of harvested land, assuming an average daily diet of 2,000 calories, or 730,000 per year; total production will be expressed in terms of billions of persons fed for a year).

Since our yield data are predicted values from a regression equation, yield trends in the predicted values (due to trending weather) and yield trends in observed yield data (due to weather and technology) will not match. Also, the variance of the predicted values will be lower as it excludes residual variance. To correct for this, we use global yield data for 1961-2009 from the FAO statistical database to calibrate our predicted yield values. We detrend both series, fitting log-yield to a quadratic time trend (pooling all 1,600 observations for each year of predicted values), and use the difference in trend values for the year 2000 to adjust the mean value for each year of predicted values. Then we scale the variance of the predicted values, using the proportional difference in residual variance for the overlapping years (1961-2009)[6]. With the predicted yield values appropriately

[5]We keep year fixed at 2000, so our yield data are weather-induced deviations from average yield in 2000.

[6]Specifically, we scale the deviations from the mean in our forecasted yields by the ratio of the standard deviation

adjusted, we generate a yield distribution for each year from 2000-2080 ($t = 0$ for the year 2000, and $T = 80$), using a discrete approximation of a normal distribution with mean and variance equal to the mean and variance of the 1,600 predicted observations for the corresponding year. Figure 1 shows hypothetical time paths of yield used in our study[7]. In general, yield trends, decreasing from 11.5 people in the year 2000 to 10.5 people in the year 2080. In addition, the 5^{th} and 95^{th} percentile yield band is getting wider suggesting higher year to year yield fluctuations in the future.

For the demand and supply parameters, we follow the existing literature. Some existing studies on empirical storage models estimate price elasticity, others assume a value; all use inelastic supply functions, and therefore have only one elasticity value that accounts for both the demand and the supply response. The estimated (and assumed) values for the combined elasticities range from -0.04 to -0.2. Roberts and Schlenker (2010) perform a reduced-form analysis in which they use contemporaneous and lagged weather shocks to identify the price elasticity of both demand and supply; they estimate elasticity of demand to be about -0.05, and elasticity of supply to be about 0.1. Following this, we use a demand elasticity of -0.04 and a supply elasticity of 0.08 for our main results (-0.12 is the middle of the range of estimates of the combined elasticities from the storage literature, and we split them this way so as to maintain the approximate absolute and relative magnitudes of the estimates in Roberts and Schlenker (2010).[8] We set the parameters of demand and supply functions such that they are in equilibrium (with zero storage) at the observed price and quantity values in the year 2000, and the elasticities are equal to the chosen values at that point. We also follow the previous storage literature in choosing the parameters for depreciation and storage cost. Cafiero et al. (2011) estimate storage cost to be equal to 0.5% of the cut-off price. Our storage cost is variable, but we set the fixed portion k_0 at 0.163, 0.5 % of the mean price in the year 2000. The variable cost k_1 is selected so that when the ratio of storage over amount on hand is greater than 0.2, $k_1 = k_0$. The selection of variable cost allows for increasing storage cost when

from observed historical yields to predicted historical yields ($\frac{SD_{Observed}}{SD_{Predicted}}$). This assumes that the residual variance is a constant proportion of yield variance, as mentioned above.

[7]Note that our yield predictions only account for the changes in weather variables as projected by the climate models; CO_2 effects are not included

[8]We report additional results for the entire range from -0.04 to -0.2 for the combined elasticities as a sensitivity check.

inventories get really high and retain the number of storage cost parameter to one. We assume zero depreciation, and an interest rate of $r = 0.02$ (we also report results for $r = 0.05$). [9]

We solve the stationary storage model for the yield distribution in 2080, assuming that climate and therefore yield will stabilize at that point, and the distribution will remain stationary. Once we have the price function for 2080 we solve for the price function for each year from 2079 back to 2000, proceeding backwards one year at a time as described in the previous section. We also solve the stationary model using the yield distribution for the year 2000 for counter-factual comparison.

Once we have storage demand and price functions for each year, we are ready to simulate two hypothetical price time-series. We first draw 101 random yield observations from the distribution for the year 2000. We use a starting value of no storage so that in period one, the amount on hand is equal to the harvest. Given the amount on hand, we can subsequently solve for price, consumption, production, land, and inventories in the first period using the storage demand function assuming no yield shift in the model.[10] Then, with inventories from the first period and yield in the second period, we can find all the other variables in the second period, and continue this way until we get to the final period. In order to avoid bias associated with the selection of starting value, we discard the first 20 observations. The remaining 81 observations give us the hypothetical price path from year 2000 to year 2080 as if nothing has changed in the model. Because the price path and other variables of the model depend on inventories and amount on hand, and these are influenced by random shocks, we simulate this price path 1,600 times to obtain a distribution of prices for each period of the baseline scenario. In the non-stationary case, we use the value of amount on hand in year 2000 from the baseline scenario as our starting value. We then simulate a price series similarly to the baseline case, but this time using the relevant price function for each year of the non-stationary case, as solved for above. This gives us a new price path, reflecting the market reaction to the anticipated supply shift.

[9] Cafiero et al. (2011) find that food storage decay rate gets really close to zero once they increase the grid of amount on hand.

[10] In implementation, we also express land as a function of amount on hand. Therefore, given amount on hand, we can find price and land at the same time.

4 Results

Figure 2 shows the price functions for the non-stationary storage model for the years 2000, 2040, and 2080 for our baseline scenario. The demand and supply elasticities are set at -0.04 and 0.08 respectively; the interest rate is 0.02. The mean price and quantity when there is no storage are 6.164 billion people and 32.558 dollars.[11] The kink represents the cutoff for storage demand or stockout price (the point where the storage arbitrage condition holds with equality). The segment to the left of the kink then, is where current price is too high and all available supply is consumed. The segment to the right of the kink represents consumer demand plus storage demand. The stockout price is shown for the year 2000, and is equal to $37.2. All of the price functions in transition time lie between the price functions for years 2000 and 2080. The closer to year 2080, the higher a price function will be in Figure 2.

Figure 3 depicts storage demand and prices under our main scenario of demand and supply elasticities. As a result of decreasing future yield, we see price increase from 34 dollars in 2000 to 67 dollars in 2080. In addition, storage is also increasing along the entire transition path.[12] Storage theory predicts that a spike in current price would lead to less storage, not more. However, in this scenario, expected future price is growing along the adjustment path as yields decline, providing increased expected profit from storage. Because of expected higher profit, storage is actually tracking with expected price, which leads to a lower level of present supply, and increased upward pressure on the overall price level.

Figure 4 shows the relationship between the yield and price distributions. We see that price is increasing as yield trend declines over time. Moreover, increased yield fluctuation also leads to increasing price volatility, as we would expect.

In Figure 5 we display how the price paths could be affected by the assumptions regarding the ratio of the demand and supply elasticities. (All scenarios represent a combined absolute elasticity

[11] At the price of 32.558 dollars (year 2000) to buy one year worth of calories for one person, the world market will provide enough food to feed 6.164 billion people.

[12] Note that this should be interpreted only as a correlation between the two trends. Our model does not replicate the level of observed inventories because we allow for the possibility of a stock-out, which never happens in reality. As the main focus of this paper is on food price and welfare, this shortcoming of the model is of little importance.

equal 0.12, and we vary the relative magnitudes). We also include the baseline case of no anticipated yield change. In general, price increases, and becomes more volatile when there is anticipated yield shift in the system. In addition, price volatility increases more than price level, in relative terms, regardless of the elasticities assumption. This indicates that while storage increases immediately in response to the increased expected profit, dampening price volatility, higher yield variability still passes through to price volatility eventually. Another noteworthy fact from Figure 5 is that prices increase more with more volatility when demand becomes less elastic. One explanation is that in our model, demand responses to spot price immediately while the supply response is delayed until the next period. Therefore, when yield declines, consumption decreases immediately while the increased production will not be realized until the next harvest time which leads to higher price and price volatility in the current period.

Figure 6 shows the relative unimportance of the interest rate assumption on mean price and standard deviation of price, respectively (though to the extent that interest rate does have an effect over the range of the various elasticity parameters, it tends to have a greater impact on price volatility than it does on level).

Figure 7 shows the time path of production and consumption. We see that consumption is always a little lower than production, and production is more volatile, reflecting the supply-side factors driving variability, and that inventories are accumulating over time in anticipation of higher expected future price.

Next we look at the net impact of increased food prices resulting from the forecasted shift yield distributions, on both consumer and producer welfare.[13] Because we assume that demand does not change over time, we simply calculate the net impact on consumer welfare using the linear demand curve in the year 2000, and price and consumption for each year from 2000 to 2080. For producers, we compute the welfare based on the assumption that land response to expected future price does not change over time (i.e. stays at the level in year 2000). For year 2000, the supply curve is

[13]Because of the arbitrage condition where storage only happens when current price equals to expected futures price minus storage cost, the surplus for storers should be equal to zero.

expressed as:

$$Q_{2000} = a_{2000} + b_{2000} * E_{2000}(P_{2001}),$$

where a and b are the parameters of the supply curve. Because supply equals land times yield, the slope the land function for year 2000 for any hypothetical path of yield j will be $\frac{b_{2000}}{yield^j_{2000}}$. In order to ensure that land response to expected future price does not change over time, the slope of the supply curve of any year t is calibrated as: $b_t = \frac{b_{2000}}{yield^j_{2000}} \times yield^j_t$. Using this slope of the supply curve, the quantity produced, and the price generated from our storage model, we can find the intercept a_t and the producer surplus for each year t.

Figure 8 shows the five year moving average of producer and consumer plus for demand elasticity of -0.04, supply elasticity of 0.08, and interest rate of 0.02. It shows a clear downward trend for consumer surplus and upward trend for producer surplus. However, the mean decrease in consumer surplus is bigger than the increase in producer surplus. By the year 2080, consumer surplus has been lowered by 166 billion dollars in compared with 2010 while producer surplus only increase by 132 billion dollars in the same time period resulting in welfare loss.

Table 1 shows the net welfare loss, in terms of billions of person fed, for the years 2020, 2040, 2060, and 2080, compared to the year 2000 for different scenarios of supply and demand elasticities. Across scenarios we see that the mean welfare loss ranges from 0.18 billion to 0.20 billion people by the year 2020. Average welfare loss is also increasing over time, reaching 1.34 billion people in 2080. The standard deviations of welfare loss are bigger than the mean (and increase over time), indicating that while we have welfare loss on average, it is possible to have welfare gain. However, the coefficients of variation of welfare loss are getting smaller over time, and results from our simulation indicate that welfare loss is three times more likely to happen than welfare gain.[14]

Another noteworthy fact from Table 1 is that the more inelastic is demand, the higher is the mean welfare loss. This is related to the lag in supply response, and our earlier findings that prices increase as demand gets less elastic. When price increases, consumer surplus decreases right away through reducing consumption. Producers on the other hand, do not have control over either land

[14]Because of the stock-out on the price functions, the distributions of price and welfare are not normal even though yields follow normal distributions.

or yield realization because the planting decision was made one period prior and yield realization is random.

Next, examine the extent to which price and welfare changes are affected by yield trend vs. yield volatility. We generate two new sets of yield data. The first one has the same yield levels as in year 2000 for all the years between 2000 and 2080, but the changes in yield volatility as in the predicted yield data. The second set has constant variance held fixed at the level in year 2000, while yield trend declines. Figure 9 shows mean and standard deviation of price under both cases. We see that mean price increases the most when both yield trend and volatility are changing over time. If only yield variability is increasing, the change in mean price is at the lowest, fluctuating around the mean price level in the year 2000. However, without the increasing price path, storage will not increase to dampen price volatility as seen in the other two cases. Hence, this case has the most price volatility, as shown. If only yield trend is changing over time, storage will increase in response to the increasing price, resulting in the lowest price volatility, as shown.

Table 2 shows the welfare loss under all three cases. We see that welfare loss is at its highest when both yield trend and volatility change. Similar to our earlier findings, by 2020, if both yield trend and volatility change, the world would have welfare loss equivalent to food for 200 million people annually. When only yield trend is changing, welfare loss reduces to food for 170 million people, and if only yield variability increases, welfare loss is food for 150 million people. In addition, as we move further away from the year 2000, the mean welfare loss when only yield volatility changes decreases compared to the two other cases, but has the highest variance because price volatility is highest in this case.

5 Conclusion

This paper is the first to incorporate a supply response into an empirical competitive storage market, and solve a dynamic case using non-stationary yield distributions. We find that price level and volatility do increase over time in response to decreasing yield, and increasing yield variability, as is expected from climate change. While we lend little credence to the specific forecasted value of prices in the distant future, we do find that the current price immediately jumps notably upon incorporation of expectations of future changes in yield distribution.

We find that land supply and storage demand both increase in response to increasing expected future prices, but not to a sufficient degree as to maintain current levels of production and consumption. Decreasing production and consumption translates into a decrease in consumer surplus, and a smaller increase in producer surplus, indicating dead-weight loss. While our estimates are sensitive to the particular assumptions regarding elasticity of demand and supply, our welfare calculations are based on elasticities that generate simulated price effects in the conservative end of the range of effects that we estimate.

This has significant distributional implications. On a household level, many net food buyers in developing countries are in the lower end of the income distribution (i.e. the urban poor); in this case, the result would be a direct transfer from the poor to the rich. On a national level, this looks like a transfer of income, and perhaps wealth, from poor food-importing countries to already rich, food-exporting countries like the U.S. This is a troubling consideration in the context of international climate negotiations.

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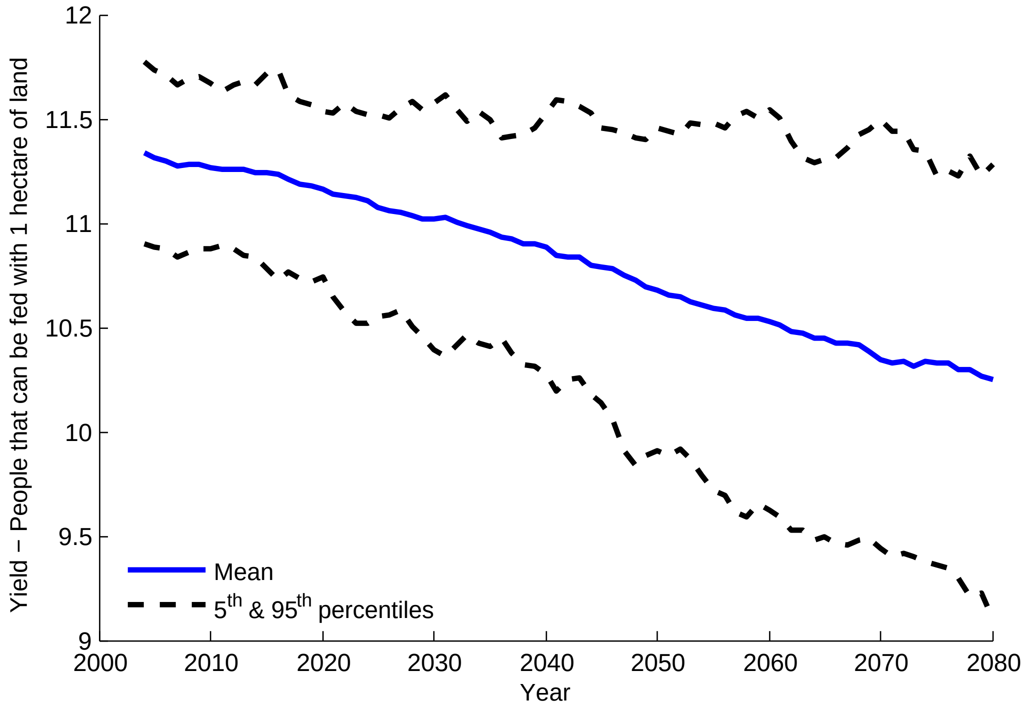
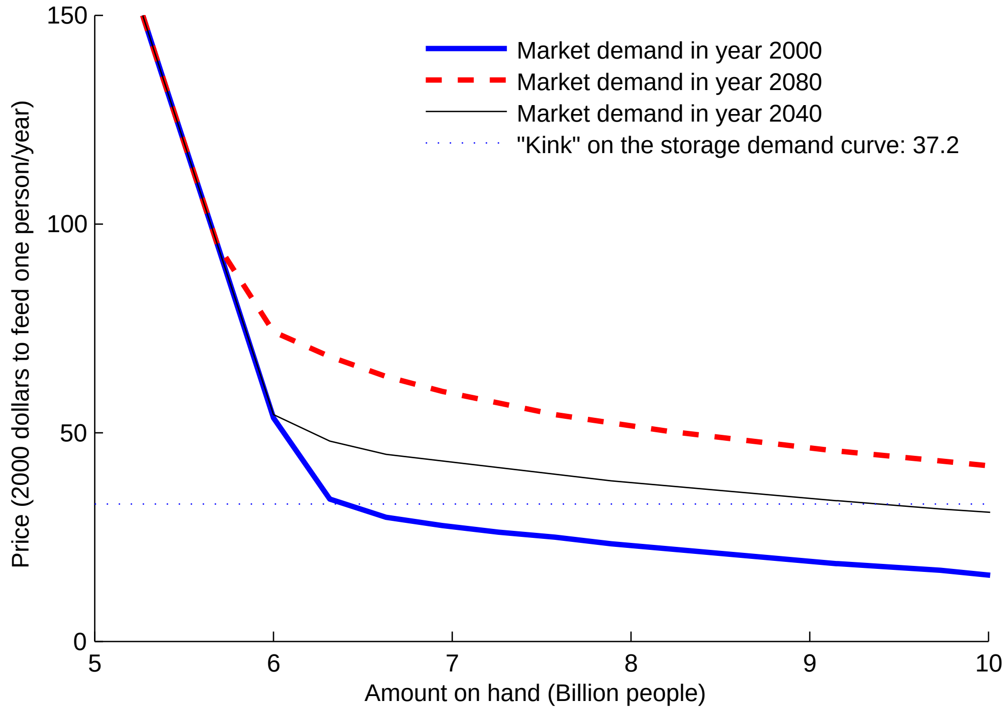
Figure 1: Aggregated Hypothetical Future Crop Yields



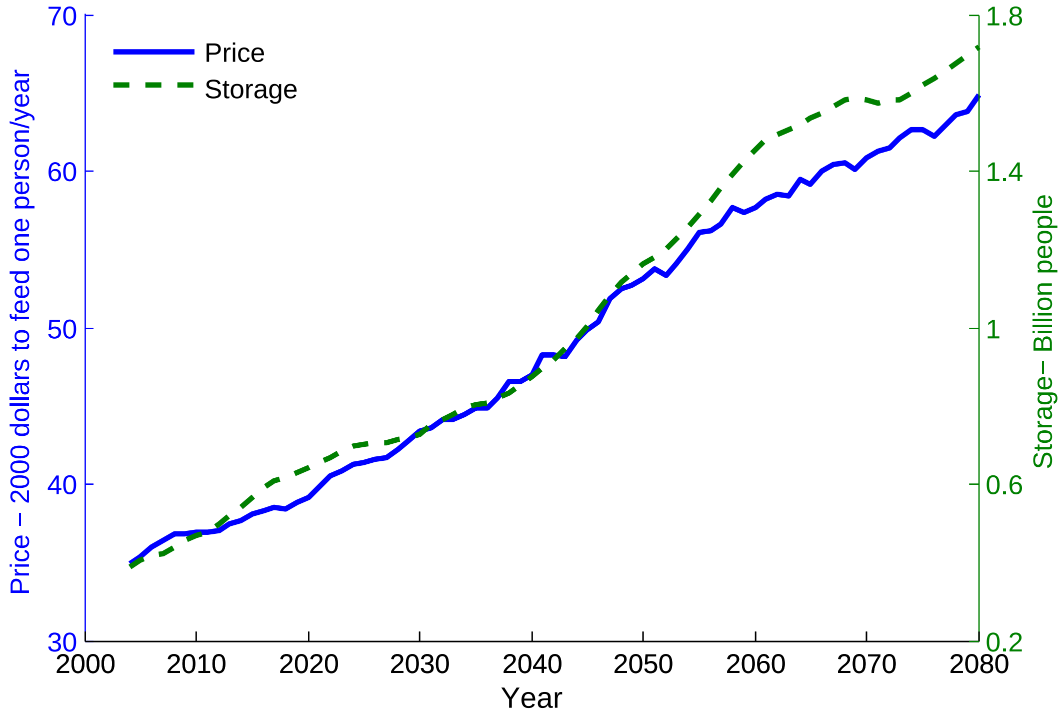
Notes: Figure shows five year moving average of hypothetical future crop yields.

Figure 2: Storage Model in Anticipation of Future Climate Change (ED=-0.04, ES=0.08)



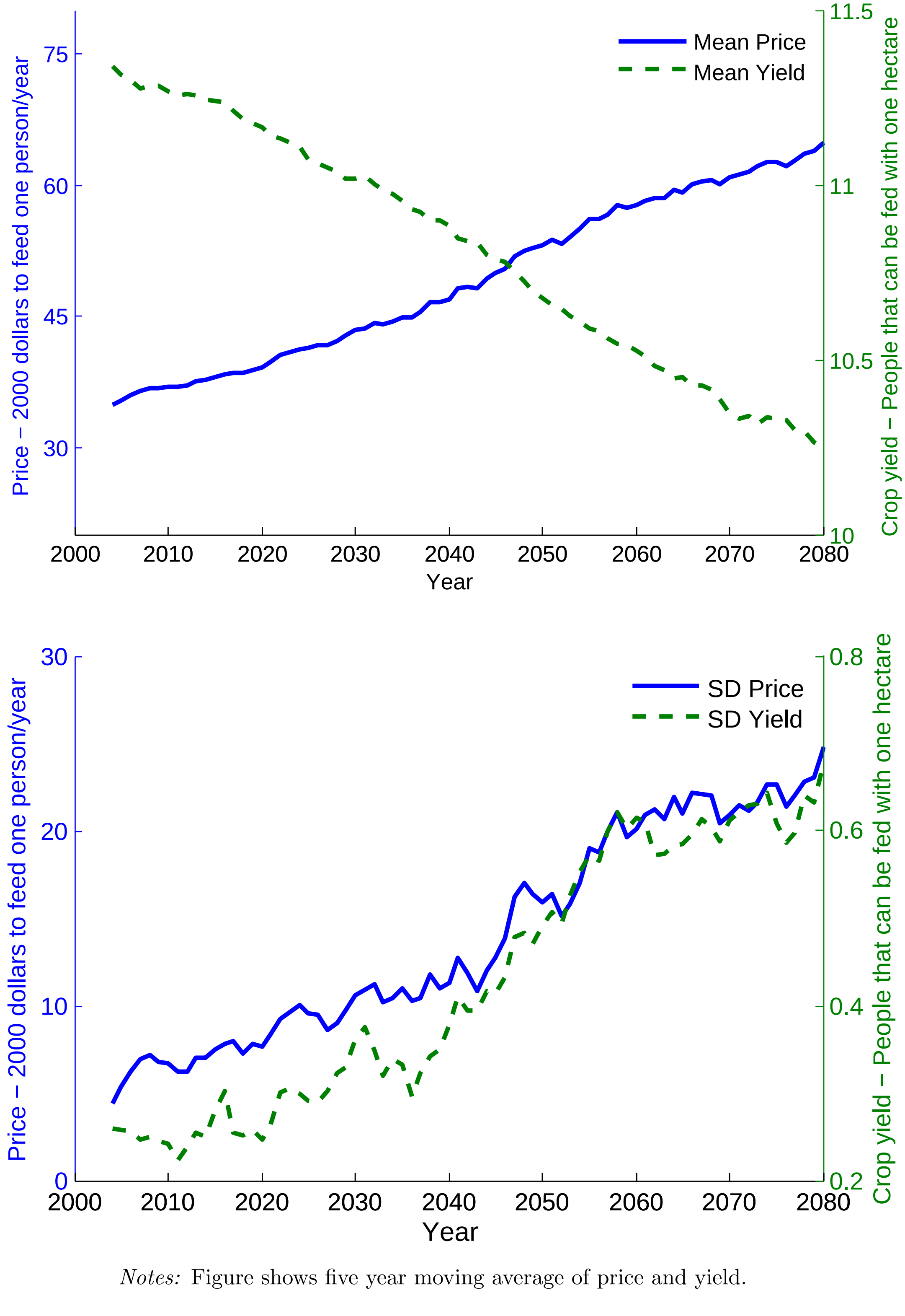
Notes: Market demand is the summation of consumer demand plus storage demand. The storage demand function is solved using constant storage cost of 0.163, interest rate of 0.02. The range of amount on hand are from 0 to 20 with 50 grid points of which 30 are clustered around the mean quantity of 6.164. All subsequent figures use the same storage cost of 0.163.

Figure 3: Price vs Storage in Anticipation of Future Climate Change (ED=-0.04, ES=0.08)



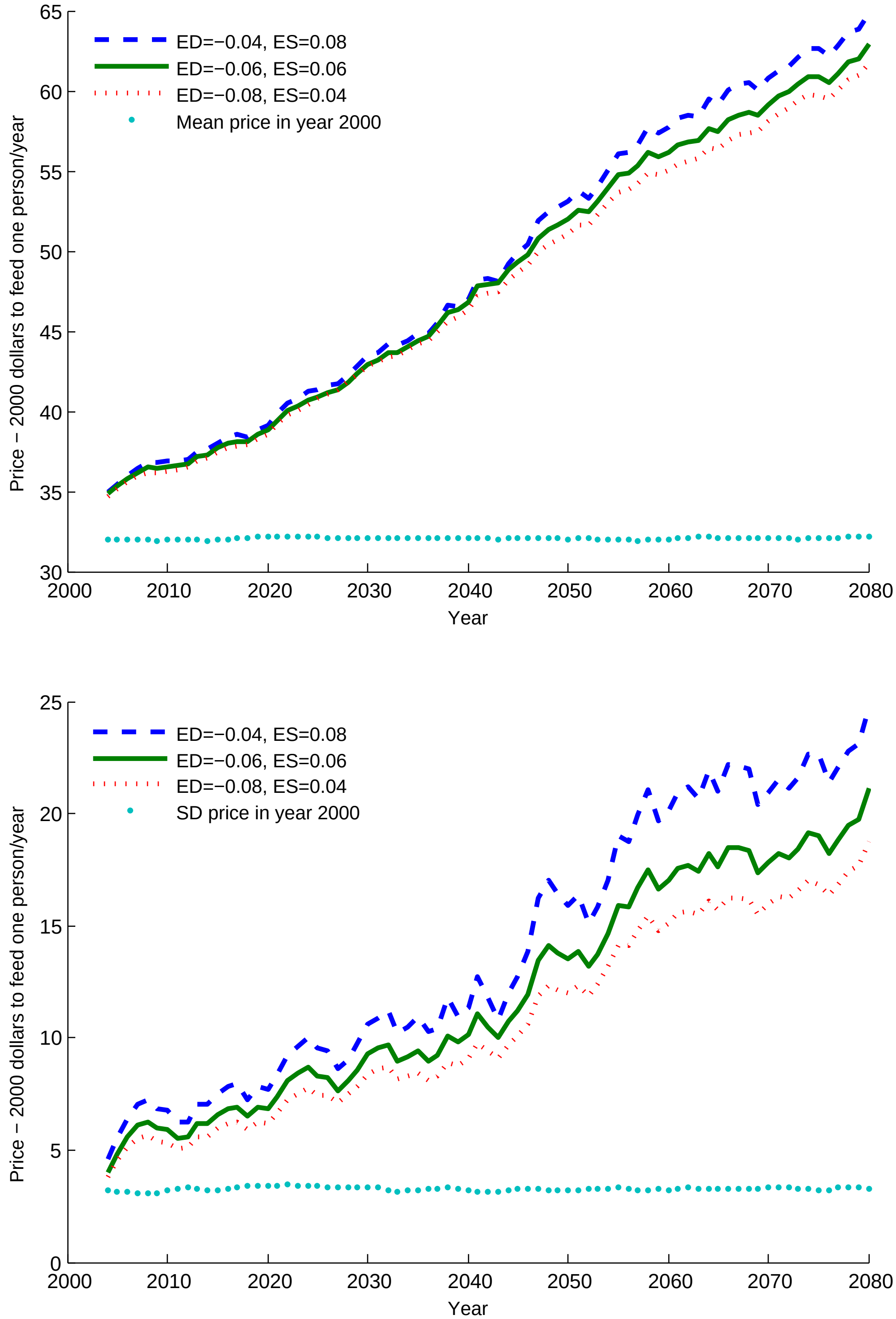
Notes: Figure shows five year moving average of mean price and mean storage.

Figure 4: Price vs Yield in Anticipation of Future Climate Change (ED=-0.04, ES=0.08)



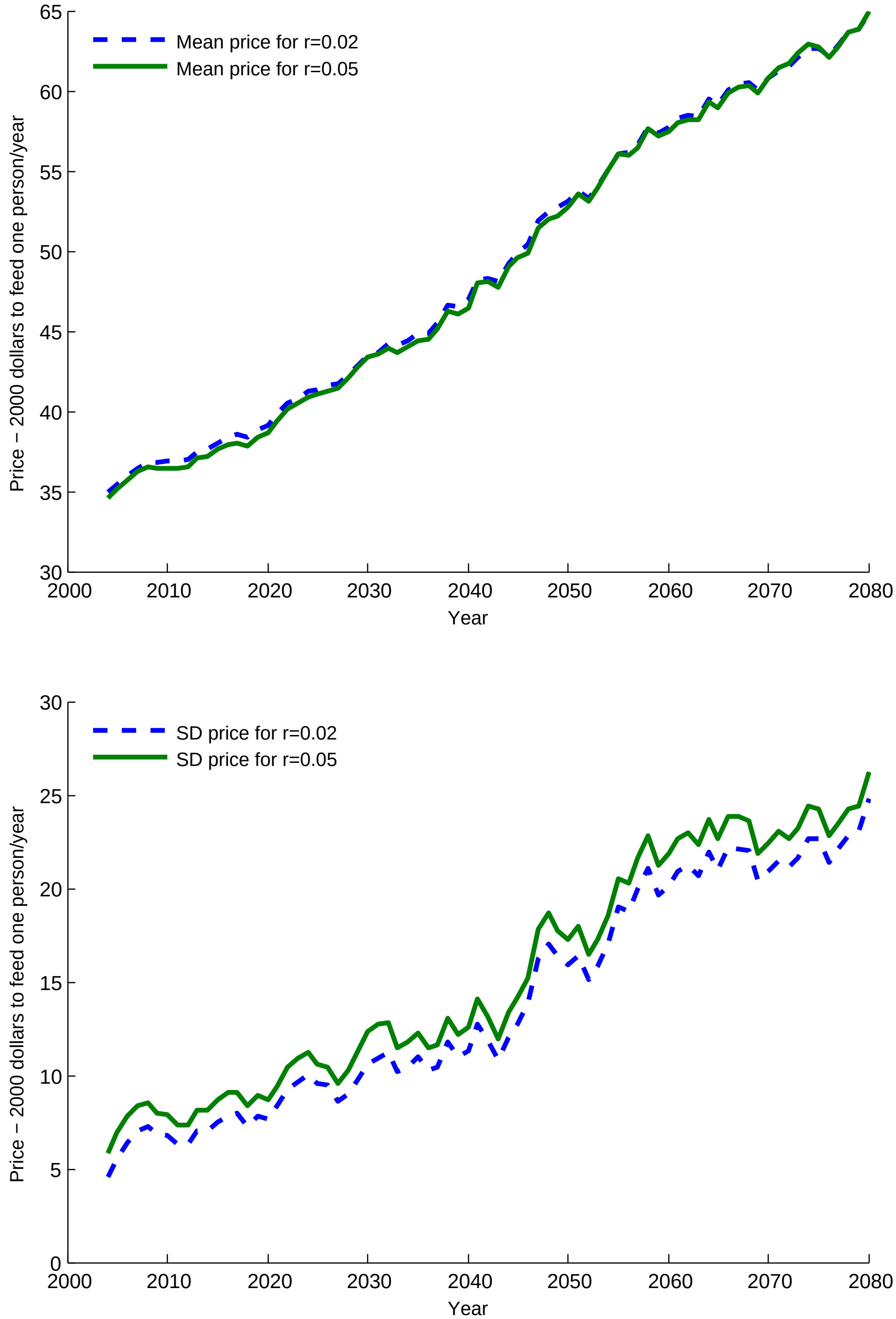
Notes: Figure shows five year moving average of price and yield.

Figure 5: Mean and SD of Price in Anticipation of Future Climate Change



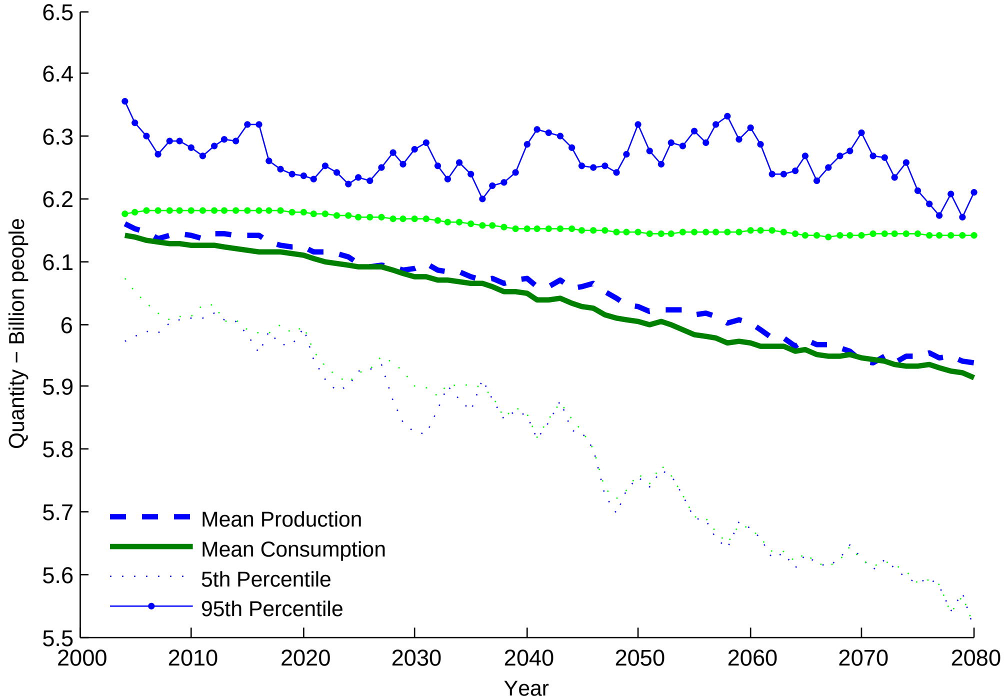
Notes: Figure shows five year moving average of price over different scenarios of elasticities. Upper panel is mean price and lower panel is standard deviation of price.

Figure 6: Mean and SD of Price With Different Discount Rate (ED=-0.04, ES=0.08)



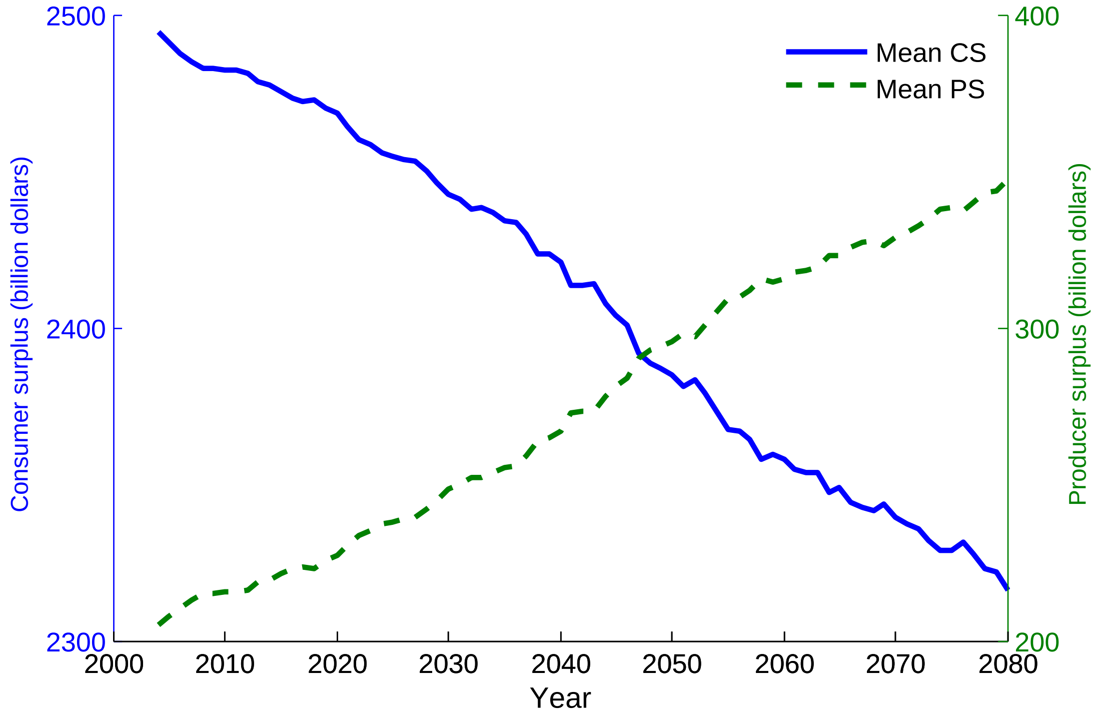
Notes: Figure shows five year moving average of price over different scenarios of discount rate. Upper panel is mean price and lower panel is standard deviation of price.

Figure 7: Production and Consumption in Anticipation of Future Climate Change (ED=-0.04, ES=0.08)



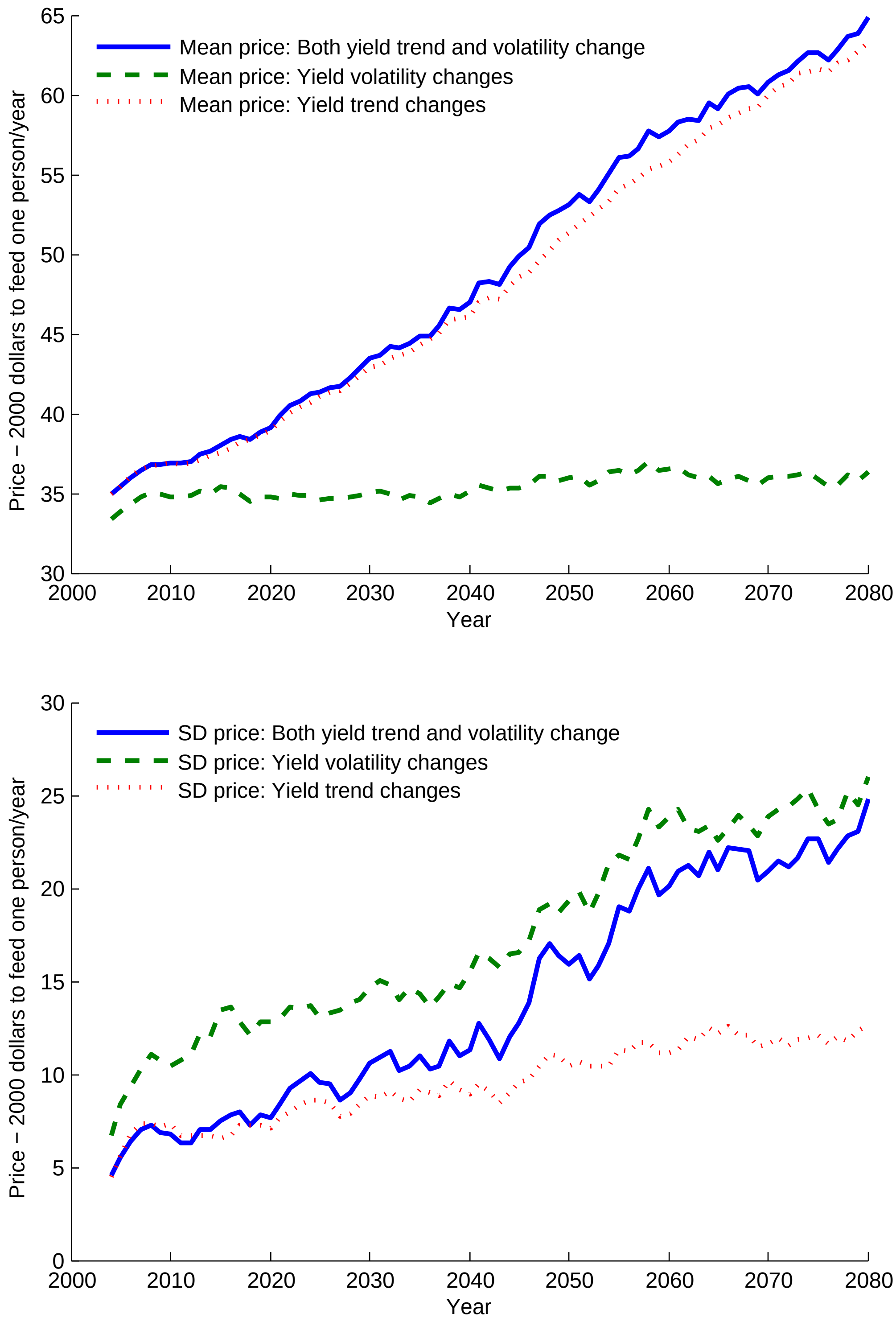
Notes: Figure shows five year moving average production and consumption.

Figure 8: Social welfare



Notes: Figure shows mean consumer and producer surplus over 1600 hypothetical paths of yield distributions. Data generated using demand elasticity equals -0.04, supply elasticity equals 0.08, and interest rate of 0.02.

Figure 9: Mean and SD of Price Under Yield Trend and Yield Volatility (ED=-0.04, ES=0.08)



Notes: Figure shows five year moving average of price path under the impact of yield trend, yield volatility, and both of them. Upper panel is mean price and lower panel is standard deviation of price.

Table 1: Welfare Loss From Lower Future Yield Distribution (Billion People)

Scenarios	**Year**			
	2020	**2040**	**2060**	**2080**
ED=-0.04, ES=0.08	0.20	0.48	1.03	1.34
	(0.43)	(0.56)	(1.52)	(1.90)
ED=-0.06, ES=0.06	0.19	0.47	0.89	1.20
	(0.41)	(0.49)	(1.10)	(1.45)
ED=-0.08, ES=0.04	0.18	0.45	0.83	1.11
	(0.39)	(0.46)	(0.92)	(1.20)

Notes: Table shows welfare loss in compared with year 2000 in terms of billions of people that can be fed. Mean and standard deviation in parenthesis are reported.

Table 2: Welfare Loss by Yield Trend and Yield Volatility (Billion People, ED=-0.04, ES=0.08)

Scenarios	**Year**			
	2020	**2040**	**2060**	**2080**
Yield trend and volatility change	0.20	0.48	1.03	1.34
	(0.43)	(0.56)	(1.52)	(1.90)
Yield volatility changes	0.15	0.18	0.35	0.38
	(0.40)	(0.52)	(1.02)	(1.21)
Yield trend changes	0.17	0.44	0.80	1.08
	(0.34)	(0.37)	(0.64)	(0.72)

Notes: Table shows welfare loss in compared with year 2000 in terms of billions of people that can be fed. Mean and standard deviation in parenthesis are reported.

Appendix

Table 3: Mean and SD of Price Over All Scenarios (r=0.02)

Scenarios	**Year**				
	2000	2020	2040	2060	2080
ED=-0.15, ES=0.05	33.08	36.57	41.39	46.53	50.54
	(2.61)	(4.77)	(6.05)	(10.85)	(12.82)
ED=-0.10, ES=0.10	33.14	36.78	41.87	47.72	52.02
	(2.76)	(5.46)	(7.20)	(13.43)	(16.13)
ED=-0.05, ES=0.15	33.31	37.09	41.89	50.06	54.51
	(3.51)	(6.47)	(8.44)	(20.55)	(22.57)
ED=-0.08, ES=0.04	33.71	39.66	47.52	56.67	63.35
	(3.42)	(7.81)	(10.07)	(18.73)	(22.52)
ED=-0.06, ES=0.06	33.84	39.84	48.12	58.08	65.06
	(3.66)	(8.49)	(11.30)	(21.65)	(26.43)
ED=-0.04, ES=0.08	33.86	40.14	48.23	60.19	67.47
	(4.02)	(9.25)	(12.73)	(27.23)	(31.75)
ED=-0.03, ES=0.01	38.91	56.13	77.47	104.75	122.56
	(5.57)	(19.22)	(25.93)	(50.22)	(62.08)
ED=-0.02, ES=0.02	39.96	56.63	79.94	110.36	130.33
	(7.30)	(21.57)	(30.35)	(61.73)	(77.30)
ED=-0.01, ES=0.01	40.00	57.97	80.80	121.59	142.23
	(7.82)	(24.62)	(35.74)	(93.69)	(105.80)

Table 4: Mean and SD of Price Over All Scenarios (r=0.05)

Scenarios	**Year**				
	2000	2020	2040	2060	2080
ED=-0.15, ES=0.05	32.82	36.36	41.44	46.35	50.47
	(3.47)	(5.22)	(6.85)	(11.39)	(13.33)
ED=-0.10, ES=0.10	32.87	36.54	41.69	47.59	51.93
	(3.93)	(6.16)	(8.31)	(14.40)	(16.90)
ED=-0.05, ES=0.15	32.58	36.78	41.74	49.87	54.66
	(4.87)	(7.72)	(9.66)	(22.49)	(24.51)
ED=-0.08, ES=0.04	33.28	39.18	47.55	56.31	63.34
	(4.91)	(8.65)	(11.23)	(19.70)	(23.44)
ED=-0.06, ES=0.06	33.46	39.44	48.03	57.82	65.04
	(5.40)	(9.54)	(12.80)	(23.10)	(27.46)
ED=-0.04, ES=0.08	33.50	39.73	47.76	60.12	67.64
	(6.25)	(10.68)	(14.07)	(29.54)	(33.74)
ED=-0.03, ES=0.01	35.83	53.81	76.66	103.33	122.86
	(8.65)	(22.24)	(29.04)	(52.85)	(63.64)
ED=-0.02, ES=0.02	36.23	54.43	79.28	109.61	130.60
	(9.75)	(25.16)	(34.35)	(65.47)	(79.90)
ED=-0.01, ES=0.01	36.48	56.03	79.79	121.59	143.57
	(11.02)	(29.29)	(40.21)	(101.21)	(112.13)

Table 5: Welfare Loss From Lower Future Yield Distribution (Billion People, r=0.02)

Scenarios	**Year**			
	2020	**2040**	**2060**	**2080**
ED=-0.15, ES=0.05	0.16	0.40	0.68	0.89
	(0.35)	(0.39)	(0.69)	(0.89)
ED=-0.10, ES=0.10	0.17	0.41	0.74	0.97
	(0.38)	(0.44)	(0.87)	(1.11)
ED=-0.05, ES=0.15	0.19	0.42	0.94	1.15
	(0.42)	(0.51)	(1.53)	(1.74)
ED=-0.08, ES=0.04	0.18	0.45	0.83	1.11
	(0.39)	(0.46)	(0.92)	(1.20)
ED=-0.06, ES=0.06	0.19	0.47	0.89	1.20
	(0.41)	(0.49)	(1.10)	(1.45)
ED=-0.04, ES=0.08	0.20	0.48	1.03	1.34
	(0.43)	(0.56)	(1.52)	(1.90)
ED=-0.03, ES=0.01	0.24	0.67	1.38	1.96
	(0.52)	(0.70)	(1.66)	(2.31)
ED=-0.02, ES=0.02	0.27	0.72	1.62	2.28
	(0.58)	(0.81)	(2.28)	(3.16)
ED=-0.01, ES=0.01	0.29	0.78	2.30	2.99
	(0.67)	(1.05)	(4.63)	(5.52)

Notes: Table shows welfare loss in compared with year 2000 in terms of billions of people that can be fed. Mean and standard deviation in parenthesis are reported.

Table 6: Welfare Loss From Lower Future Yield Distribution (Billion People, r=0.05)

Scenarios	**Year**			
	2020	**2040**	**2060**	**2080**
ED=-0.15, ES=0.05	0.17	0.41	0.69	0.90
	(0.36)	(0.41)	(0.70)	(0.91)
ED=-0.10, ES=0.10	0.17	0.42	0.75	0.98
	(0.40)	(0.48)	(0.91)	(1.16)
ED=-0.05, ES=0.15	0.20	0.44	0.98	1.20
	(0.48)	(0.58)	(1.67)	(1.91)
ED=-0.08, ES=0.04	0.19	0.46	0.84	1.12
	(0.39)	(0.48)	(0.93)	(1.24)
ED=-0.06, ES=0.06	0.20	0.48	0.91	1.21
	(0.42)	(0.53)	(1.14)	(1.50)
ED=-0.04, ES=0.08	0.21	0.49	1.07	1.38
	(0.46)	(0.60)	(1.63)	(2.02)
ED=-0.03, ES=0.01	0.26	0.69	1.40	1.97
	(0.51)	(0.71)	(1.68)	(2.34)
ED=-0.02, ES=0.02	0.28	0.75	1.65	2.32
	(0.59)	(0.85)	(2.35)	(3.25)
ED=-0.01, ES=0.01	0.33	0.81	2.45	3.14
	(0.72)	(1.13)	(4.98)	(5.92)

Notes: Table shows welfare loss in compared with year 2000 in terms of billions of people that can be fed. Mean and standard deviation in parenthesis are reported.