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Methodological and Ideological Options

Automatic Responses of Crop Stocks and Policies Buffer Climate Change Effects on Crop Markets and Price Volatility

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ABSTRACT

Climate change has the potential to affect crop prices and price volatility. However, the economic models used in prior assessments largely do not include known, automatic, stabilizing factors. Crop storage can stabilize prices and U.S. crop policy tends to provide support that moves opposite prices. We quantify effects of circa 2050 climate forcing on the inter-annual variability of U.S. Corn Belt corn and soybean yields using statistical crop models and climate scenarios from regional and global climate models. Climate change generally reduces mean yields and increases the inter-annual variability of yields in the Midwestern U.S. Using these yield impacts and an economic model with automatic market stabilizers, we find only modest increases in price volatility. Although individual producers and states are negatively affected by the yield reductions, the aggregate effect for all corn and soybean producer returns can be positive because of price increases. Moreover, agricultural policies based on price levels or revenue variation offset some of the impacts of market variation on farm income. Our results differ from other recent results and temper concerns that increasing climate instability necessarily translates to greater uncertainty about agricultural commodity uses, including as food and biofuels, in the near future.

1. Introduction

Climate change might have critically important consequences for crop yields and markets, land use, and food security. Climate change has been projected to increase yield volatility by as much as 50% (Chen et al., 2004; Diffenbaugh et al., 2012; Urban et al., 2012), suggesting potential impacts on crop market volatility. Attention has been given mostly to yield changes, farm- or region-specific response, or to yield-induced price level changes, but most studies have not explicitly represented crop stocks or policies that respond automatically to changing market conditions thereby buffering effects of climate variability or other environmental shocks on markets and producer revenues (e.g. Adams et al., 1995; Attavanich and McCarl, 2014; Barnwal and Kotani, 2013; Calzadilla et al., 2013; Campbell et al., 2006; Kandulu et al., 2012; Mearns et al., 1997; Sandford and Scoones, 2006; Tack et al., 2012).

We represent the impacts of climate change on crop yields in a key growing region and on market volatility, taking into account automatic policy and market responses that have not yet been represented in this literature. Historical data show inverse correlations between corn price and stocks, and corn price and related government expenditures (Fig. 1). Crop stocks are defined as the amount in storage at the end of one marketing year for use in later years. Holding grain stocks is not free, incurring costs of the facilities and delaying receipts from sales, yet is a key mechanism for smoothing consumption over time despite production fluctuations (Westhoff, 2010). Stocks are held from the harvest to be used throughout the remainder of the marketing year and also held for sales in the subsequent marketing year in the event the

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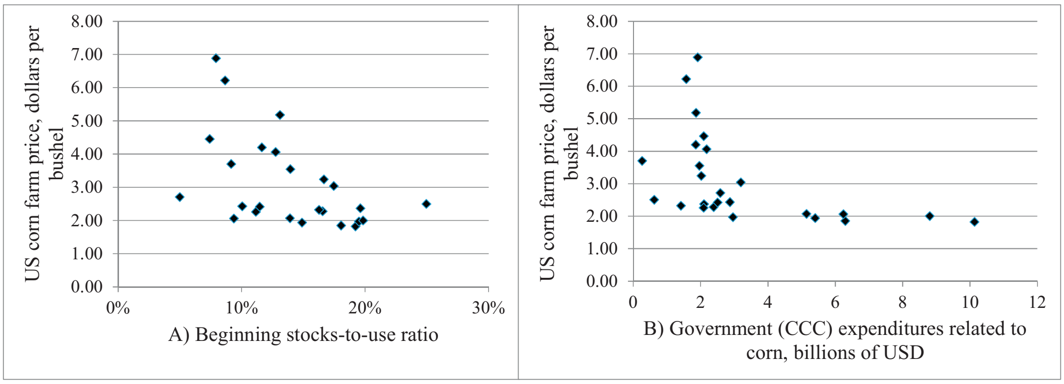

Fig. 1. Inverse relationship of United States corn price with stocks and policy expenditures.
Sources: USDA NASS (*www.nass.usda.gov*) for corn price, ERS data (*www.ers.usda.gov/data/* feedgrains) for quantity data that are used to calculate stocks-to-use ratio, and FSA CCC Budget Essentials (*http://www.fsa.usda.gov/about-fsa/budget-and-performance-management/budget/ccc-budget-essentials/index*) for expenditure data.

next harvest is poor. Grain stockholding has motivations and costs that might not be present in the cases of some other agricultural products. For example, livestock products like meat and butter require refrigerated storage facilities and can be produced throughout the year, in most cases, whereas crop storage is not refrigerated and also relates to the surges of production at harvest time as well as uncertainty about the next harvest.

A cursory examination of global corn production and use shows that year-to-year fluctuations in production do not cause similar variations in consumption (Fig. 2). At times when production is higher than usual, prices are typically pushed down and stocks grow. In years when production is low, prices are pushed up and existing stocks are drawn down without being replenished. Thus, although weather and other factors cause production to swing from one year to the next, changes in stocks allow consumption to follow a more stable path. If stock holding were not possible, then global consumption would have to equal global production. In this hypothetical case, grain price is the factor that would drive consumption up or down: in a low production year, price would have to rise until enough consumers are discouraged from buying the grain that no more is consumed than produced; and in a good year the price would have to fall until consumers are induced to buy as much as is consumed. An economic model that omits automatic stock responses would tend to over-estimate market price volatility impacts of climate variability. Yet, some important models used in climate impacts studies do not represent stocks or policies explicitly and therefore could err in projections of future market volatility.

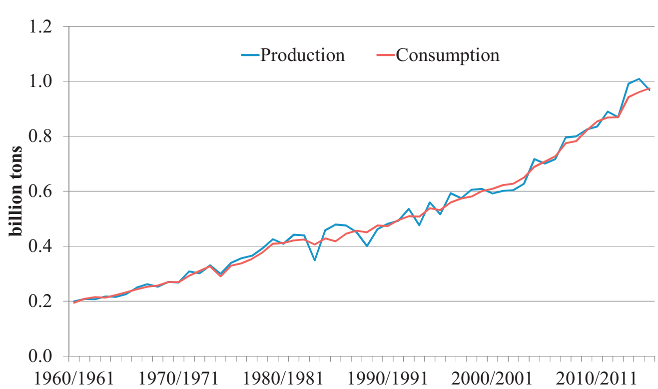

Fig. 2. World corn data show greater year-to-year variation in production than in total consumption because of stocks.
Source: USDA/FAS PSD View (http://apps.fas.usda.gov/psdonline/psdhome.aspx).

At the same time, many U.S. agricultural policies are tied to market events: some pay out only if market prices fall below trigger levels and others might pay if returns or prices decrease. Therefore, these policies can have different effects in the context of a large price decrease as compared to a large price increase (Fig. 1). Moreover, studies of market volatility induced by climate change to date have not examined producer revenue impacts taking into account yield, price, and subsidy changes.

A ground-breaking study assessed climate volatility impacts by using downscaled regional climate change estimates to project corn yield changes in the U.S. Corn Belt that, in turn, were used to adjust stochastic yield variation in a model that generates price effects (Diffenbaugh et al., 2012). The model, Global Trade Analysis Project (GTAP), typically combines commodities into broad aggregates, solves at less than annual frequency, and represents most policies as constant price wedges without the actual connections to market conditions (Narayanan et al., 2012). Diffenbaugh et al. (2012) adjust GTAP to represent annual markets and endogenous policy with significant modifications yet do not explicitly include crop stocks and this omission could bias volatility estimates (Diffenbaugh et al., 2012). Many other modeling approaches relating to climate change or other environmental factors also ignore stocks and consequently would be inappropriate tools for assessing the impacts of changing market variation, as well as the consequences for prices and producer receipts (Brouwer et al., 2008; Dellink et al., 2011; Freire-González et al., 2017; Gallai et al., 2009; Ianchovichina et al., 2001; Melathopoulos et al., 2015; O'Ryan et al., 2005; Salami et al., 2009).

We argue that assessments of climate change impacts on agricultural markets should ideally take into account stabilizing stock responses to prices, and assess the combined impact of yield, price, and government support responses on crop producer revenue. Here we use a market model that includes automatic stock and policy responses to estimate how U.S. Corn Belt corn and soybean yield changes driven by circa 2050 climate change affect the level and variability of corn and soybean market prices and quantities. First, we estimate climate change effects on the average and variance of corn and soybean yields for the mid-21st century. Second, we introduce these yield changes into a stochastic economic model to estimate market impacts, taking automatic responses of stocks and policy intervention into account. Our methods expand the possibilities of conducting economic analysis of climate change across multiple crops simultaneously, and provide estimates of the role of climate impact buffering due to crop storage and government support. Our results highlight the importance of crop stocks and policies in assessments of climate change impacts on crop price variability and agricultural producer receipts.

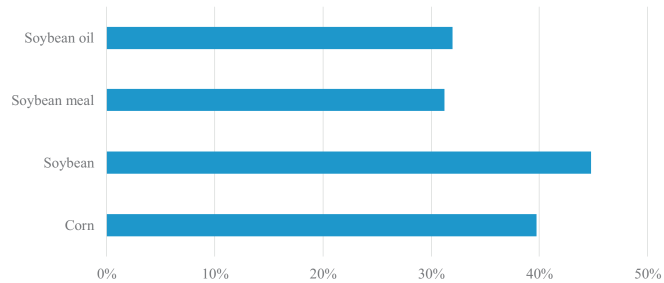

Fig. 3. U.S. corn and soybean production as shares of world total. Source: USDA/FAS PSD view data (*www.fas.usda.gov*).

2. Materials and Methods

2.1. Climate Data and Yield Estimation

We quantify the effects of circa 2050 climate forcing on corn and soybean yields across a range of statistical crop models and six regional climate model simulations for seven Midwestern U.S. states (Iowa-IA, Illinois-IL, Wisconsin-WI, Minnesota-MN, Indiana-IN, Ohio-OH, Missouri-MO) that together account for 64% and 65% of U.S. corn and soybean production. We take an empirical modeling approach in which historical crop yield and climate data are used to train a set of statistical crop models, and then regional climate change projections are used to forecast crop yield changes for the middle of the 21st century.

This region is critically important for global corn and soybean production. The U.S. corn and soybean production accounted for 40–45% of the world total from 1982/83 to 2012/13, and about a third of global soybean meal and oil production in this period (Fig. 3). While these proportions trended lower over this period and one could consider these crops as part of aggregates that included related goods, like other feedgrains or oilseeds, these data suggest that the U.S. accounts for a substantial share of the world market. The seven states of this study accounted for a majority of U.S. corn and soybean production, as noted above, so yield fluctuations in this region have implications for global production and markets.

We parameterized the statistical crop models for each state using state-level USDA National Agricultural Statistics Service (NASS) yield and 50-km climate training data for the years 1982 to 2012 that was aggregated to the state scale by weighting according to crop area geographic distribution within each state. We generated the climate training data by running the regional climate model (RCM), RegCM4.3 (Giorgi et al., 2012), with boundary condition forcing from global reanalysis data (NCEP/DOE Reanalysis 2) (Kanamitsu et al., 2002) (Supplemental material). The time series anomaly for this RegCM4.3/NCEP simulation was not significantly different from observation-based climate data (CRU, 2008), and showed 59% agreement in precipitation values and 73–75% agreement in temperature values.

To quantify potential change in crop yields with climate change, we used historical and future RCM output from the North American Regional Climate Change Assessment Program (NARCCAP) database (Mearns et al., 2007; Mearns et al., 2009; Mearns et al., 2012; Mearns et al., 2013) to drive the parameterized crop models. The NARCCAP RCM simulations were driven by boundary conditions from six alternative GCM simulations, providing an ensemble of scenarios. The simulation years included historical (1968–1999) and mid 21st century (2038–2069) periods. In the Corn Belt, NARCCAP RCM temperature and precipitation changes tended to be similar to GCM-projected changes, but more pronounced in summer when variance among NARCCAP projections was dominated by the RCMs and unexplained noise (Mearns et al., 2013). In particular, the RCMs projected stronger drying than the GCMs, in this agriculturally important region. To correct for differences between the training and hindcast/forecast climates, we applied a quantile-based bias correction to the NARCCAP model output.

We examined a range of statistical yield models by using different permutations of predictor variables, selecting the model form and variables that provided good out-of-sample forecasts for the Midwest U.S. region. Each quadratic yield model was composed of three predictor variables with one month for monthly maximum temperature (T_{max}), one month for monthly minimum temperature (T_{min}), and one month for monthly precipitation (Precip). To avoid multicollinearity, we only used monthly climate predictors that were not highly correlated ($r < 0.3$).

$$Yield = a_0 + a_1 year + a_2 year^2 + a_3 T_{max} + a_4 T_{max}^2 + a_5 T_{min} + a_6 T_{min}^2 + a_7 Precip + a_8 Precip^2 \tag{1}$$

We performed a bootstrap test to quantify out-of-range uncertainty resulting from the fact that some NARCCAP future climate projections were outside of the range of the historical climate training data (Supplemental material). We selected the best five crop models (for each crop and state) based on a historical out-of-sample error analysis and used this ensemble of best crop models to quantify climate impacts (see Supplemental material). Each of the five models used different combinations of Tmax, Tmin, and/or precipitation for different months, resulting in different dependencies on climate at particular times of year. Alternative formulations of the statistical model (e.g., degree days and interaction terms) have also been used but have been shown to produce similar results as the quadratic formulation used here (Urban et al., 2012).

2.2. Market Model

The model we choose adds to the science of market volatility induced by climate change by representing explicitly automatic stock and policy responses to market conditions. We used the stochastic, partial equilibrium model, FAPRI-MU, for our analysis, which includes U.S. agricultural commodity and biofuel markets and policies, and stockholding behavior that responds automatically to market prices (Gerlt and Westhoff, 2011; Thompson and Meyer, 2013; Thompson et al., 2010; Thompson et al., 2011; Westhoff et al., 2006; Westhoff and Meyers, 2010; Whistance and Thompson, 2014). Corn and soybeans and other major crops, crop products, and livestock products are represented explicitly. Other sectors and other countries are implicit, not explicitly represented. We used the version of March 2016 (Westhoff et al., 2016).

Policies are represented to reflect how they work, including payment rates that depend on market conditions (Westhoff and Gerlt, 2012, 2013). As regards the biofuel mandates, or the Renewable Fuel Standard, the policy is represented with overlapping mandates for different fuels from corn starch, vegetable oil, or other feedstocks subject to eligibility conditions outlined in law and implementing regulations. Renewable Identification Numbers (RINs), which are used for complying with the mandate, are estimated in terms of their generation from domestically used biofuels, use for compliance, and storage or rollover (Thompson et al., 2010). The potential for certain types of substitution within mandates, such as biodiesel displacing corn starch ethanol if prices warrant, and the potential for RIN storage to help smooth price swings are elements included in this representation that should moderate price volatility relative to at least some other research (e.g. Diffenbaugh et al., 2012). Exogenous data include macroeconomic conditions and petroleum prices, which are varied to generate many market simulations each under different conditions. The model output includes area planted to specific crops, yields, market quantities and prices for the commodities explicitly represented, measures of farm income, consumer expenditures on food, and government program costs. Model projections span a decade and are used for scientific investigation and also by practitioners, including policy makers (Meyers et al., 2010).

The stochastic results reflect hundreds of simulations for various macroeconomic and weather conditions (Westhoff et al., 2006). Randomly drawn input data are typically based on historical variations, with the method generally intended to reproduce historical distributions and also correlation among related factors. This method of model simulation addresses some forms of uncertainty and has also been found to reproduce market price volatility (Westhoff, 2015). To introduce the effects of climate change on crop yields, the distributions of corn and soybean yields are shifted based on the impacts estimated using the statistical yield models described above. National area equations are used for the stochastic model, so the impacts of the yield shocks are weighted by the projected shares of the represented states in total supply of these crops.

The model results do not represent projections for a specific set of years, but rather provide estimates of crop market sensitivity to climate change within a realistic policy context, including automatic policy responses to yield changes. The economic model assumes a 10-year planning horizon common in agricultural decision making, with confidence in the policy and market structure to the 2025/26 marketing year. The mid 21st c. climate change and yield scenarios reflect potential changes over a ~70 year period from 1968–1999 to 2038–2069.

Our economic model has two relevant distinctions relative to other models commonly used for climate change analysis, including impacts on price variability. First, we recognize that policy intervention depends on market conditions. This choice carries with it a sharp difference from the fixed parameters or values used to represent agricultural policies in the alternative approaches (Calzadilla et al., 2013; Diffenbaugh et al., 2012; Hertel, 1997; Ianchovichina et al., 2001; Narayanan et al., 2012; Paltsev et al., 2015). Many U.S. agricultural policies have long been explicitly tied to market outcomes (Fig. 1), even without making any assumptions about new policy choices that could also influence markets (Johansson et al., 2006).

Our model reflects the relationship between market conditions and support provided by U.S. agricultural policies in contrast to the fixed parameters used in many previous studies, as noted above. Existing U.S. crop policies include base area payments, crop insurance, and the marketing loan program. Support tied to base area can be provided under Price Loss Coverage or Agricultural Risk Coverage. In the first case, the payment depends on whether market price of the base crop falls below a legislated trigger and, if so, by how much. In the latter case, the payments depend on whether revenues associated with the base crop fall by at least a certain amount relative to recent revenues, usually assessed at a county level, in which case a payment can make up some of the difference. These payments are tied to corn and soybean base area so eligibility depends on how area was planted historically and the payments are consequently not tied to current outputs In the model, the allocation of base area by crop and by program is tracked and the amount of payments is estimated based on price relative to trigger or changes in revenues, as required, and then allocated according to base area.

Federal crop insurance and marketing loan programs are tied to current output. The federal crop insurance program might have higher or lower net indemnities in any given year, but the expected value is estimated to be equal to the average net indemnities over time. The value of this subsidy is consequently dependent on the value of production, so the subsidy associated with a crop will rise or fall over time with the product of price and production of that crop. The model estimates this value and associates the value of crop insurance to the production of the associated crop, giving some incentive to producers to increase their sales. The marketing loan program results in benefits to producers if the market price falls near or below the legislated loan rate, and the amount of benefits will depend on whether a gap opens up between loan rate and price. In the model, the marketing loan program sets a floor on producer returns per unit.

These main supports tied to crop production are by no means a complete list. Cotton and dairy programs are also represented in the model and will have different effects under different market conditions, as well. The model used here allows support to move opposite prices or revenue in many cases as required by law. The treatment is consistent with long-standing patterns of support in the U.S.

The second distinction is that the model represents crop stocks explicitly using standard methods for applied policy analysis (Labys, 1973, OECD, 2007, 2015), in contrast to many climate change studies (Diffenbaugh et al., 2012; Paltsev et al., 2015; Reilly et al., 2003). Our representation of U.S. corn and soybean stocks allows stock levels to adjust to changes in prices and production. As expected from long-standing economic theory about stockholding, a very good harvest that drives down prices in one marketing year gives incentive to stockholders to increase the volume stored in expectation that price might rise if the next harvest is closer to normal. If a very poor harvest causes less production and higher prices in a marketing year, then private agents might expect that the price will fall if the next harvest is better so they will choose to hold less ending stocks. This speculative behavior represents a key factor that smooths fluctuations in prices and use over time. In our model, grain stocks at the end of a marketing year tends to move opposite the price of that marketing year and also tend to be inversely correlated with expected production of the following year, thereby representing this behavior (Supplemental material).

Diffenbaugh et al. (2012, p. 3) note that the treatment of stocks in their model "…makes it impossible to examine the interplay between increased year-on-year volatility and the private-sector incentives for accumulating stocks and releasing them in low-yield years – which will have a moderating influence on prices." However, the role of crop stocks in smoothing price and consumption volatility is well established (e.g., Newbery and Stiglitz, 1981). U.S. corn market data, for example, show an inverse correlation between price and the stocks on hand (Fig. 4).

In most instances, stock changes alleviate market pressure that would otherwise drive prices even higher in years with low production and cause an even lower price in those years with high production. A model might implicitly capture some of this stabilizing effect if aggregate demand response is calibrated to represent an average effect of both immediate uses and stock holding. A limitation is that this approach does not capture the range of stock responses, particularly omitting the potential that a period of low stocks leaves less flexibility in markets and can be associated with the potential for stronger price increases, as in 2005/06 to 2012/13, and that times with ample stocks

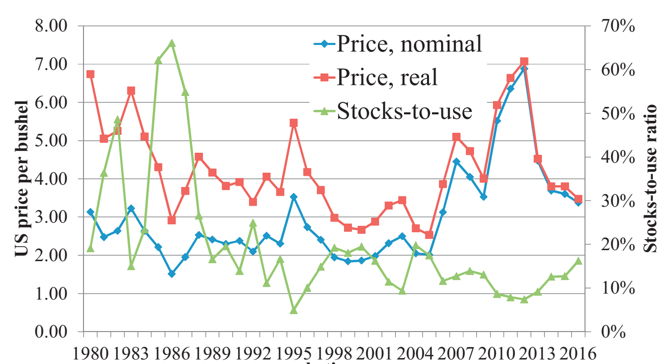

Fig. 4. U.S. corn price and stocks-to-use ratio show an inverse relationship. Source: USDA/NASS (*https://www.nass.usda.gov/*).

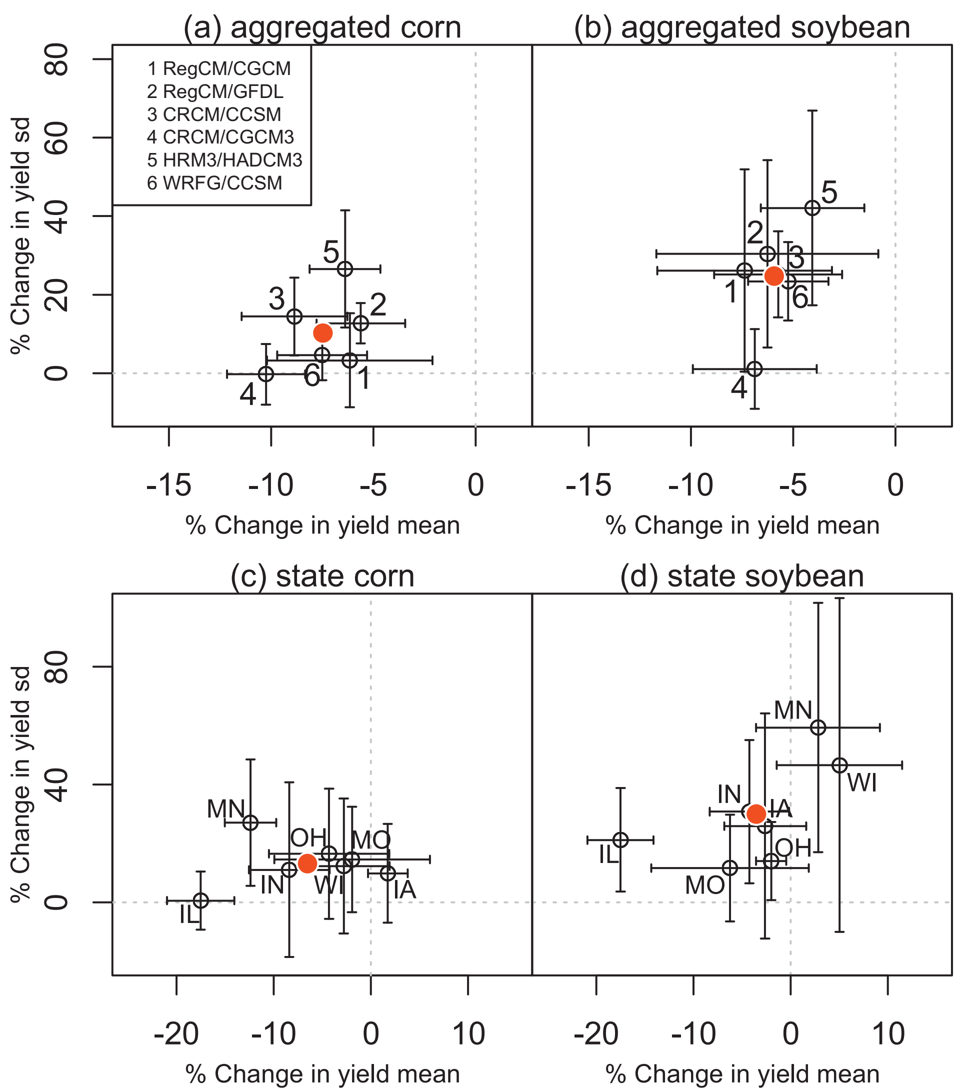

Fig. 5. Percentage change in mean yield and in yield standard deviation (sd).
Notes: Data are over a ~70 year period (1968–1999 to 2038–2069) among climate models aggregated for the seven-state study domain for corn (a) and soybean (b), and for individual states averaged across the six climate models (c and d). The error bars in (a) and (b) are 95% confidence intervals across the five statistical models while the error bars in (c) and (d) are the 95% confidence intervals across the six climate models. The red dots show the area-weighted changes in mean yield and yield standard deviation across states and climate models. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

give greater flexibility. Moreover, approaches that do not explicitly model stocks miss the dynamic carryover effect of a year with high production and low price on price and use in the subsequent year.

3. Results

3.1. Impact of Climate Change on U.S. Corn Belt Corn and Soybean Yields

The mid 21st c. climate changes reduce yields (by 8% and 6% for corn and soy) and increase inter-annual variability of yields (by 10% and 25% for corn and soy) in the U.S. Corn Belt region, with significant state-to-state variation in the change (Fig. 5). Of particular note, state differences in yield response to climate change are larger than differences among climate scenarios derived from six global-regional climate model combinations (Fig. 5). For corn, the smallest changes are projected in Iowa, the largest reductions in mean yield in Illinois, and the greatest increase in yield variability in Minnesota. For soybeans, the smallest changes are projected in Ohio and the largest reductions in mean yield in Illinois. Previous studies differ from ours in the formulation of statistical models and future climate scenarios used. Nevertheless, our results are qualitatively consistent with most previous studies, which indicate a decline in crop yields and an increase in inter-annual variability with climate warming (Porter and Semenov, 2005; Schlenker and Roberts, 2009; Urban et al., 2012). For example, our yield models project increased standard deviations of year-on-year corn and soybean yield ratios by 44.6% and 46.0% for the climate scenarios we examined (Fig. 6), about half of the increase found by Diffenbaugh et al. (2012) for corn. This suggests that future climate effects overwhelm errors that are associated with the model formulations or training data used. At the same time, prior studies of price impacts have not typically examined two major crops simultaneously, and our yield analysis shows that interannual variability in soybean yields increases more than corn yields, which has important implications for price responses of both crops (Thompson et al., 2017).

3.2. Market and Policy Response

Corn and soybean prices average 5–6% higher and are more volatile because of the Corn Belt yield shock from climate change (Table 1). The direction is consistent with Diffenbaugh et al. (2012), but the effects of climate change on price variation in our model are substantially smaller than the estimates provided by those authors. They found that climate change caused year-over-year U.S. corn price variability to increase by a factor of about 4 with a ~40-year change in climate and yields, while we found increases in price standard deviation of 13% for corn and 8% for soybeans with a ~70-year change in climate and yields. There are many reasons to expect differences in these results. The size of climate and yield shocks and fundamental supply and demand responsiveness will not be the same. Moreover, whereas previous research appears to have represented the biofuel mandate as a fixed requirement for crops

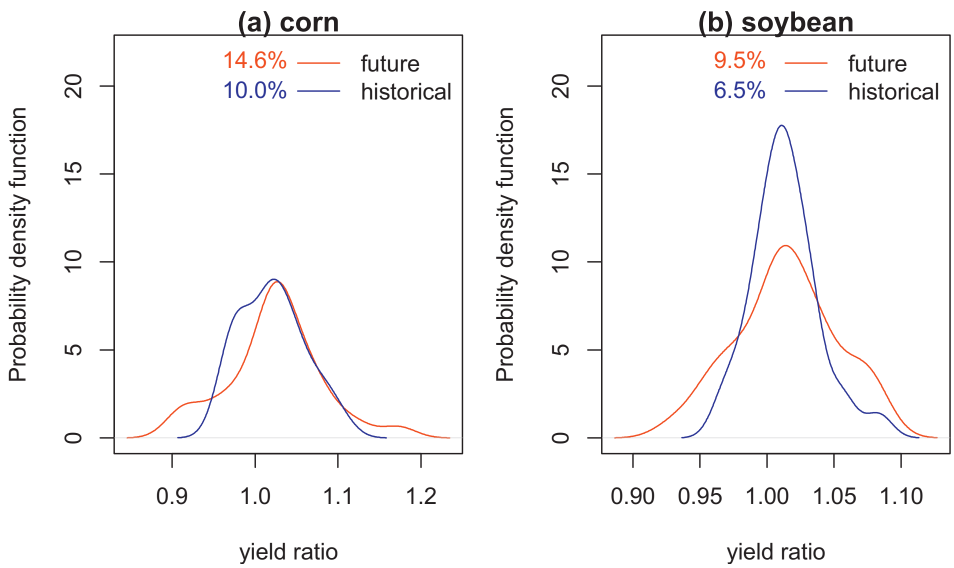

Fig. 6. Historical and future distributions of year-on-year yield ratios ($y_t = y_{t-1}$) for corn and soybean. Data span a ~70 year period, 1968–1999 for historical and 2038–2069 for future, aggregating across climate models and the seven-state study domain. The colored numbers are the mean standard deviation of yield ratios across the 30 (6 climate models and 5 crop models) crop yield projections. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Estimated effects of climate change on US corn and soybean market indicators.

	Changes from the baseline values			
	Average		Standard deviation	
Average yields, bushels per acre				
Corn	−7.0	−4%	2.3	21%
Soybean	−0.7	−1%	0.3	12%
Area planted, million acres				
Corn	0.60	1%	0.24	4%
Soybean	0.18	0%	0.13	4%
Total	0.78	0%	0.23	5%
Farm price, dollars per bushel				
Corn	0.22	6%	0.12	13%
Soybean	0.51	5%	0.21	8%
Related government (CCC) expenditures, billion dollars				
Corn	−0.22	−12%	−0.18	−7%
Soybean	−0.07	−13%	−0.07	−8%
Total	−0.29	−13%	−0.22	−7%
Producer receipts, billion dollars				
Corn	2.09	4%	0.55	5%
Soybean	1.46	4%	0.31	5%
Total	3.58	4%	0.75	5%

that would not change no matter the price shock, the model used here represents flexibility in biofuel mandates and markets caused by substitution among overlapping mandates, the ability of biofuel use in one year to help meet mandate in the next, and biofuel trade (Supplemental material). While multiple differences in model formulations could contribute to this different result, we focus on the stocks in our model as a key element.

US market impacts are moderated because the Corn Belt, although important, is not the only producing region. The effect is further moderated because of feedback from price: lower average yields cause higher prices, and the higher prices cause at least some increase in yield that partly offsets the initial shock, as well as more area planted to these crops. The yield and price changes have implications for government payments and producer revenues that are discussed below.

Price variations are approximately doubled if crop stocks are held constant (Fig. 7). Stocks of corn, soybean, soybean meal, soybean oil, and biofuel mandate compliance certificates (also called RIN rollover) are constant in this sensitivity analysis. Removing these forms of private stockholding changes market response, with demand sensitivity to price falling by one-quarter to one-half (see Supplemental text). Because stocks will no longer adjust as private agents respond to changing incentives, the price must move more than before either to coax more purchases for immediate use when supplies are high or to discourage more sales for immediate use when production is low. Consistent with our expectations, by omitting the dynamic response of crop stocks and key crop product stocks our model projects greater price variation, particularly for corn. The 90th percentile of the corn price distribution increases by twice as much with climate change if stocks do not adjust and the 10th percentile price is lower (Fig. 7).

4. Discussion

We show that certain automatic market and policy responses to changing market conditions can buffer price variability effects of climate change. Multidisciplinary efforts to determine the impacts of climate change on agricultural commodity price variability are a new area of study that expands on the better developed efforts to estimate the impacts on mean price levels. To extend scientific knowledge in this area, we used an economic model that represents how crop stocks and government expenditures depend on market conditions. This model has been used for policy analysis and focuses on year-on-year dynamics of market shocks, which are critical for examining price volatility. The findings presented here suggest that representing existing stock behavior and automatic policy responses, in addition to supply versus demand effects on price levels, represent important elements for assessing the impacts of climate change.

Climate changes that reduce yields and increase yield variability can increase average returns, here average U.S. corn and soybean producer returns. A climate shock to a crop yield that reduces supply can have a greater proportional effect on the crop price. Crop returns are the product of price and yield, so average returns will rise if the percent increase in price is larger than the percent decrease in yield. If all farmers in a key growing region lose their entire crop to poor weather, then those farmers have nothing to sell but farmers in other regions that had normal or better weather would still harvest their crop and sell at a higher price as markets respond to the lower supply. As in other models, the average effect reported here does not track each individual crop producer's case. Another reason is the natural hedge provided by a downward-sloping demand. If a supply shock forces the quantity lower, then the price will tend to rise. These ideas are also relevant in the context of climate change. If demand is fairly unresponsive to price, or inelastic, then a reduction in yield can cause a larger proportional

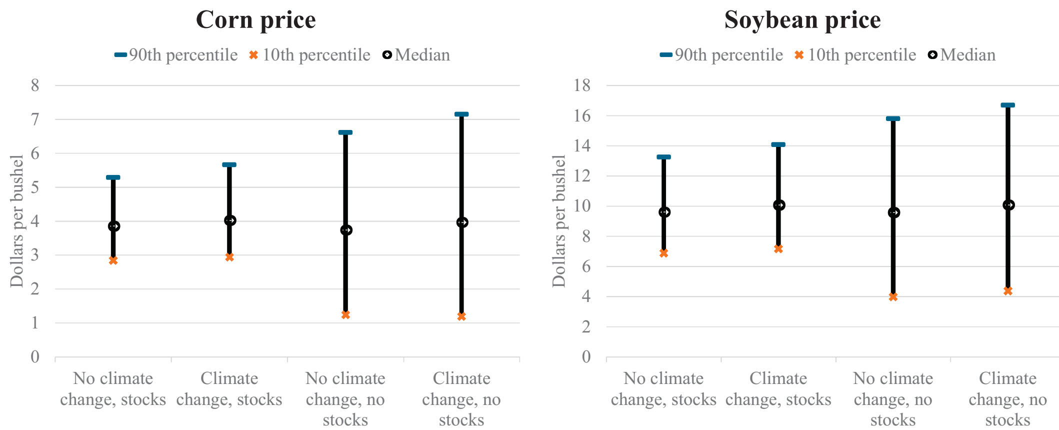

Fig. 7. Ranges from 10th to 90th percentile of US farm prices (U.S. dollars) for the final five years of the analysis from stochastic market model simulations. Note: Simulations allow or prevent stocks to respond to year-to-year yield variations for historic conditions (no climate change) and scenarios of mid 21st c. climate change in the Corn Belt. Corn price ranges are given on the left and soybean price ranges are given on the right.

increase in price. The end result reported here is higher and more variable aggregate producer receipts.

One impact that has not been adequately considered in past studies is stock holding. Lower and more variable yields and, although we do not explore the potential that climate change causes more autocorrelation in yield shocks explicitly, a greater incidence of year-over-year negative yield shocks with climate change puts pressure on crop stocks. Crop stocks have been assessed using various long-standing approaches (Brennan, 1958; Gustafson, 1958; Labys, 1973), and are generally expected to counteract market price volatility. A key potential limitation of a stock equation in the context of yield shocks is whether the increase in volatility would suggest a different stock level or response. With the changes in price variation shown here, the potential for sharply different stock holding behavior is small. Although potentially important, we do not explore the potential that climate change would increase the frequency or severity of multi-year droughts or other persistent climate departures that would cause multi-year yield impacts.

Another important aspect of market response to climate change is the policy response. While a substantial shock (i.e., outside of recent experience) to markets might render the assumption of constant policy suspect, our results highlight how existing policy causes automatic changes in expenditures on farm subsidies. Omitting these responses, which tend to work opposite the climate effects on producers, might tend to over-state the producer impacts. Notably, the US Agricultural Act of 2014 ended fixed direct payments and introduced new programs whose payouts are designed to move opposite price or revenue. Climate change effects on Corn Belt yields cause lower corn and soybean program expenditures given the estimated impacts on market receipts (Table 1). Some program payments are tied to historical base area, so associating these payments strictly with corn and soybean area production decisions could be too strong, but these payments nevertheless offset some of the market revenue changes. Looking at price alone omits an automatically offsetting response built into existing policy. Such automatic policy response is a long-standing feature of US agricultural policy; climate change analysis predicated on exogenous subsidy levels would implicitly assume a sharp change from past program design.

Our results help to address the need for research into medium-term yield and market fluctuations and uncertainty. The mid-century impacts might not be large enough to raise concerns about fundamental changes in stockholding or cropping patterns. Even mid-century yield effects on markets can be moderated by stockholding behavior and agricultural policy responses. Estimates of impacts on markets that imply larger volatility into the far future should take into account at least existing stock and agricultural policy responses, but shocks that are large enough to produce important changes in market price and revenue volatility could induce changes in stock holding behavior or the policy setting.

In sum, our results suggest that the price range and farm impacts of climate change might be overstated, perhaps quite substantially so, if markets are rendered in a way that disallows certain automatic market and policy responses. The results are likely sensitive to myriad factors, such as the size of the initial shock and the general market sensitivity to price. At the very least, our results argue for the use of multiple economic models to take advantage of their various strengths. Much as climate change estimates might be considered more reliable if based on an ensemble of models, economic analysis is probably more reliable if multiple approaches are explored in order to identify various potential avenues of price impact, some of which might exacerbate market sensitivity whereas others might naturally dampen price variations.

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Appendix A. Supplementary Data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2018.04.015.

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