Essays on the Economics of Land Use and Adaptation to Climate Change

by

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To Lesley, John, Penelope, and Evangeline

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CHAPTER 1

Land-Use Adaptation to Climate Change in the United States, 1982-2012

1.1 Introduction

The economics of climate change has matured into a multifaceted frontier of research to understand damages, mitigation, and distributional consequences across a range of nations, sectors, policies, and geographies (Burke et al., 2016). On the damage side, the social cost of carbon aggregates damages into a comprehensive measure for use in public policy analysis (Greenstone et al., 2013). In this context, adaptation by economic agents is important for estimating individual damage functions, as it will typically lower damages. This is the main idea of early research by Mendelsohn et al. (1994) on the agricultural impacts of projected climate change, which finds relatively small impacts to U.S. agriculture when allowing for adaptation. In contrast, previous research typically assumes no adaptation by holding farmer behavior constant, producing damage estimates that are biased upward.[1]

Although more than twenty years have passed since this groundbreaking study, adaptation remains relatively unexplored in the economics of climate change (Burke et al., 2016). At the same time, two methodological advances have created research opportunities relative to the Mendelsohn et al. (1994) cross-sectional approach. The first applies panel-data methods while using variation in annual temperature and precipitation to estimate economic

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[1] Mendelsohn et al. (1994) refers to this bias as the "dumb-farmer scenario" as it ignores many adaptations that are routinely made by agricultural producers.

impacts (Deschênes and Greenstone, 2007). The second approach, "long differences", exploits medium- to long-run variation in *average* weather variables over time, where changes over multiple decades serve as an approximation to climate change (Dell et al., 2012). Dell et al. (2014) state that long-difference "estimates are perhaps the closest empirical analogue to the structural equation of interest for climate change... particularly if we are interested in climate change impacts in the medium term (e.g., by 2050)." Aggregate economic output (Dell et al., 2012) and agricultural crop yields (Burke and Emerick, 2016) have been studied using the long-differences approach.

The mechanisms of adaptation to climate change - even less well studied than adaptation per se - are now being investigated. For example, Albouy et al. (2016) study location choices by U.S. households to identify their preferences over local climates. They find, in their baseline specification, that adaptation via human migration is moderately extensive: the average absolute value of the population change across public-use microdata areas is 10.3%. Despite this population change, the estimated aggregate welfare loss changes little (from 2.28% to 2.01%) when migration is included. Davis and Gertler (2015) examine the use of air conditioning for home cooling as an adaptation to higher temperatures. In their main results, adaptation is projected to generate additional carbon dioxide emissions as air conditioning (and electricity use) increase to keep pace with higher temperatures, such that a comprehensive analysis of damages with adaptation should incorporate both direct and indirect effects. In an agricultural context, changes in cropland use are suggested as an important mode of adaptation (Mendelsohn et al., 1994; Burke and Emerick, 2016). As the climate warms, for example, a farmer might grow winter wheat instead of corn due to wheat's early harvest, prior to the higher summer temperatures of July and August.[2] Yet crop choice and related cropland use have not been extensively studied as a mechanism of agricultural adaptation.

This paper examines land-use change in the United States from 1982-2012 using the long-differences approach. Substantial adjustments in U.S. land use occurred over this period. Using data from the National Resources Inventory (U.S. Department of Agriculture, 2015), total cropland decreased from 421 to 363 million acres, a change of -14% (U.S. Department of Agriculture, 2015). Meanwhile, developed land increased from 72 to 114 million acres (+59%), pastureland decreased from 131 to 121 million acres (-8%), and forestland increased from 410 to 413 million acres (+1%). If we consider change at the parcel level, turnover is even more striking. 19% of cropland in 2012 was new since 1982, while 30% of cropland in 1982 had since switched to another use. While these changes

[2]One can envision the Winter Wheat Belt in the United States migrating northward into the Corn Belt, and the Corn Belt migrating into Canada, as macro-phenomena of climate change.

were shaped by many factors, our primary research question asks whether climate had any influence. How does climate change affect land-use change in the United States?

Burke and Emerick (2016) investigate crop yields in the United States using the long-differences methodology. Their research suggests that some adaptation has occurred to maintain crop yields, although the evidence is limited. Using aggregated data by county, they do not find significant responses in total corn area or total farm area to observed climate change, but they do find a negative response to extreme heat exposure for the corn share of total farm area. However, as mentioned above, the county-level aggregation masks significant parcel-level changes. By studying land-use change at the parcel level, we directly examine the extensive margin of land use as a primary mechanism of adaptation.

Changes in climate induce changes in land use by altering the lands' potential net-returns (i.e., profit). In agriculture, for example, net-returns can be modeled as a function of price, yield, and cost, all of which can be affected by changes in climate. In Ricardian models of agricultural adaptation to climate change (Mendelsohn et al., 1994; Schlenker and Roberts, 2006), the dependent variable, farmland value, is motivated as the discounted stream of future net-returns. Given that the research finds significant effects when farmland value is regressed on climate variables, a natural question is to ask whether land use responds to climate change.

To answer this question, we use parcel-level data from the National Resources Inventory (U.S. Department of Agriculture, 2015). The NRI is a statistical survey of U.S. land-use conditions, conducted by USDA's Natural Resources Conservation Service, that covers individual land points from 1982-2012. We can observe a specific point in 1982 and track its land use and land quality through 2012. Due to confidentiality restrictions, we do not observe the actual location of the point, only the county in which it is located. We combine the NRI data with fine-scale weather data from Annan and Schlenker (2015), which consists of daily temperature and precipitation data on a 2.5-by-2.5 mile grid across the continental U.S. between 1950-2014. We use the weather data to construct climate measures at the county level.

Previous research used NRI point data in national models of land use (Lubowski, 2002; Lubowski et al., 2006; Lewis and Plantinga, 2007; Lubowski et al., 2008; Haim et al., 2011; Radeloff et al., 2012; Claassen et al., 2013; Hamilton et al., 2013; Lawler et al., 2014). In these studies, NRI point data are combined with estimates of net-returns for each broad category of land use (cropland, pasture, CRP, forest, range, and urban) to estimate probabilities of land-use change between each category. The focus is typically on using market returns to simulate the effects of different policies on land use. For example, topics address the land use implications of: carbon sequestration (Lubowski, 2002; Lubowski et al., 2006), forest defragmentation (Lewis and Plantinga, 2007), markets and farm-policy (Lubowski et al., 2008; Radeloff et al., 2012), protected lands (Hamilton et al., 2013), and ecosystem services (Lawler et al., 2014). However, only Haim et al. (2011) considers the effect of climate. Haim et al. (2011) uses previously estimated climate-induced changes in yields, prices, and urbanization from integrated assessment models to predict future climate effects. Still, the effect of climate on land use is not explicitly estimated in the model.

Our approach, in contrast, uses climate information directly. We begin by exploring the long-differences framework in the context of land-use decisions. With this method, changes in land-use-related outcomes are regressed on observed changes in climate between two periods covering, in this case, thirty years. As with panel data methods that use annual weather variation, we are able to avoid time-invariant omitted variables bias. Long-difference estimates have the additional benefits of being identified from variation in actual climate change and implicitly accounting for medium-run (or longer) landowner adaptations (Burke and Emerick, 2016; Dell et al., 2014).

Many of the outcomes of interest can be analyzed using long-difference-transformed variables in OLS. The decision to irrigate, for example, is formulated as a binary dependent variable, for which we estimate a linear probability model. We estimate similar models describing broad land-use transitions, e.g., the decision to switch into or out of cultivated cropland. With these models, the consistency of our estimates depends on the exogeneity of observed changes in climate, a point which is rigorously defended in Burke and Emerick (2016). We investigate whether those results hold in our context.

Our preliminary results suggest that changes in land use correspond closely to estimates of both climate-change effects and weather effects on crop yields. Burke and Emerick (2016) and Schlenker and Roberts (2009) both estimate that additional time spent in temperatures above 29°C is harmful for corn yields, while temperatures below are beneficial. Similarly, we find that additional time above 30°C increases the probability of switching away from cropland, while additional time below 30°C increases the probability of switching into (or not switching away from) cropland.

Making accurate projections about future land use is difficult using models that have been reduced to binary decisions as there are more than two land uses of interest. For this problem, we are exploring models of multinomial choice for which probability estimates are guaranteed to remain between zero and one.[3]

The paper continues as follows. Section 1.2 describes empirical models and issues related to land-use adaptation to climate change. Section 1.3 describes the data. Section 1.4

[3]We are currently extending this research to estimate nested logit models in the spirit of Lubowski et al. (2006) and related papers. Results are not yet available.

presents preliminary analysis, the main results, and several robustness checks. Section 1.5 offers concluding remarks.

1.2 Estimating Land-Use Adaptation to Climate Change

1.2.1 The Long-Differences Model

Our model is designed to evaluate, in a probabilistic sense, the extent to which landowners have adapted land use in response to observed changes in climate. That is, we want to estimate the impact of changes in different climatic variables on the probability of land-use change. We focus on modeling binary discrete choice outcomes.

To begin, we define variable y_{ik} such that $y_{ik} = 1$ if landowner i chooses land use k, and $y_{ik} = 0$ otherwise. Examples of binary outcome variables are choosing to grow crops, converting cropland to pasture, installing irrigation, or developing the land. As in Dell et al. (2014), we want to approximate the following unknown relationship for each outcome variable:

$$y_{ik} = f(\mathbf{C}, \mathbf{X}) \tag{1.1}$$

where $\mathbf{C}$ is a vector of climatic variables and $\mathbf{X}$ is a vector of other characteristics that are held constant.

As discussed in both Dell et al. (2014) and Burke and Emerick (2016), one option is to use cross-sectional variation in observed climate to explain land-use outcomes at a fixed point in time. For example, Mendelsohn et al. (1994) introduced the "Ricardian" method that regressed farmland values on average temperature and precipitation using only cross-sectional variation across counties.[4] Applying the Ricardian framework to land-use outcomes, we specify the following linear approximation of Equation (1.1) for a given cross-section:

$$y_{ik} = \alpha_k + \beta_k \mathbf{C}_i + \gamma_k \mathbf{X}_i + \epsilon_{ik} \tag{1.2}$$

There is wide variation in climate across U.S. states and counties, which likely has an effect on local land-use decisions. The cross-sectional model represents a long-run equilibrium that explicitly makes use of this variation. However, these models present several challenges to isolating climate impacts. As discussed in Dell et al. (2014), the cross-sectional model may capture other long-run historical processes related to land and

[4] See also Schlenker et al. (2006).

agricultural development, or even colonialism, that were influenced in part by variation in climate. If our estimates implicitly embody these long-run processes, then they will be less useful for understanding the effects of climate change in the near future.

Additional concerns relate to unobserved factors that are correlated with climate, influence land-use decisions, and are important for projecting future climate impacts. Examples may be unobserved soil quality (Deschênes and Greenstone, 2007), water supply and irrigation potential (Schlenker et al., 2005, 2006), or agglomeration effects associated with the development of local upstream or downstream industry (McWilliams and Moore, 2016a). To remove confounding effects of irrigation, studies often restrict analysis to U.S. counties east of the 100^{th} meridian, which approximates the boundary between irrigated and rainfed crops (Schlenker et al., 2005, 2006; Schlenker and Roberts, 2009; Burke and Emerick, 2016).

More generally, some researchers have turned to panel methods in order to avoid omitted variables bias and isolate climate impacts in the absence of other correlated factors (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). For example, with panel data covering a range of years, the standard "within" estimator removes all time-invariant confounders during the sample period. The cost of this method is that climatic variables measuring long-run averages are, generally, not identified. Instead, researchers use short-run weather variation, often arguing that weather-based impacts represent an upper bound for climate impacts in the long-run when agents have more ability to adapt (Deschênes and Greenstone, 2007). The panel model version of Equation (1.2) is:

$$y_{itk} = \alpha_k + \beta_k \mathbf{W}_{it} + \gamma_k \mathbf{Z}_{it} + \mu_i + \theta_{rt} + \epsilon_{itk} \tag{1.3}$$

where $\mathbf{W}_{it}$ is a vector of weather outcomes for landowner i at time t. The vector $\mathbf{Z}_{it}$ contains time-varying observable controls, while all time-invariant controls are absorbed by the unit fixed effects, μ_i. It is common to also include time-varying regional fixed effects, θ_{rt}, where i is spatially located in r, in order to capture short-run confounding factors not absorbed by μ_i (Deschênes and Greenstone, 2007; Dell et al., 2014). However, since weather outcomes are spatially correlated, the use of highly localized time-varying regional fixed effects can significantly reduce the identifying weather variation. As shown in Fisher et al. (2012), this can lead to significant attenuation bias if local variation in the weather variables is partly due to measurement error.

Dell et al. (2014) and Burke and Emerick (2016) caution that although panel methods solve some problems associated with the cross-sectional method, short-run weather impacts may neither be representative of long-run climate impacts nor even provide a reliable bound. Although the ability to adapt in the long run will tend to mitigate impacts, intensification effects such as persistent drought, may push in the opposite direction.

As an alternative, Dell et al. (2012) develop the long-differences approach, which Burke and Emerick (2016) apply by regressing changes in agricultural outcomes on actual changes in observed climate over twenty years.[5] In their study, for example, they calculate county-level changes in average corn yield between 1978-1982 and 1998-2002 and regress on measures of change in average growing degree days and precipitation over the same period. Following Burke and Emerick (2016), our long-differences model is constructed by first taking n-year averages of the right-hand-side variables in Equation (1.3) at two time periods, t_0 and t_1. This equation for each time period is equivalent to Equation (1.2) where $\mathbf{C}_i = \bar{\mathbf{W}}_i$ except for the addition of $\bar{\mu}_i = \mu_i$ and $\bar{\theta}_{rt}$.[6] The two equations are then differenced, producing

$$\Delta y_{ik} = \beta_k \Delta \bar{\mathbf{W}}_i + \gamma_k \Delta \bar{\mathbf{Z}}_i + \Delta \bar{\theta}_r + \Delta \bar{\epsilon}_{ik} \tag{1.4}$$

where the constant, α_k, and the panel-level fixed effects, μ_i, cancel out. In the differenced model, the time-varying regional fixed effects, θ_{rt}, become regional fixed effects. This model is our starting point for the empirical analysis, and in our robustness checks, we consider a range of combinations of t_0, t_1, and n such that $t_1 - t_0 \geq n$.[7] In practice, we do not use any time-varying controls, Z_i, except for the climate variables.

1.2.2 Connection to Ricardian Climate Change Models

Equation (1.4) is a reduced form representation of the effect of climate change on land-use outcomes. We do not specify or restrict the pathways in which climate can affect land use. With an assumption about the exogeneity of observed climate change, which is defended

[5]The long-differences approach has been used in other climate-related research as well. Hornbeck (2012) applies a variation for estimating the long-run impacts of the Dust Bowl on land values, revenues, and land-use outcomes in counties that experienced varying degrees of soil erosion. However, in that study, treatment occurs in the base period and all explanatory variables represent values at t=0 (i.e., pre-Dust Bowl).

[6]Another way of thinking about the long-difference transformation is simply differencing the cross-sectional relationship in Equation (1.2), which has first been specified for two distant time periods, while also acknowledging that the error term contains the panel-level and time-varying regional fixed effects, i.e., $\epsilon_{itk} = \mu_i + \theta_{rt} + u_{itk}$.

[7]Note that since y_{itk} is binary, Δy_{ik} can take three possible values: -1, 0, or 1. In practice, we estimate versions of Equation (1.4) where the estimation sample is restricted to land with a common land use in the base period, t_0. For example, we might define $y_{itCrops} = 1$ for land that is cropland and $y_{itCrops} = 0$ otherwise. If we restrict the sample to land that was cropland at t_0, then Δy_{iCrops} takes values of -1 or 0. The differenced variable can then be rescaled as a traditional 0-1 binary variable without loss of generality, such that $\Delta y_{iCrops} = 0$ for land that switched out of crops and $\Delta y_{iCrops} = 1$ for land that remained in crops. This model would estimate the probability of land staying as cropland. Alternatively, using the same original outcome variable, $y_{itCrops}$, we could restrict the sample to land that is not cropland at t_0 and estimate the probability of switching into cropland.

below, we can use OLS to estimate the causal effects of this reduced form relationship. However, it is worth pointing out that Equation (1.4) also has connections with more theory-driven models that underly the Ricardian analysis going back to Mendelsohn et al. (1994).

The central assumption in the Ricardian framework is that landowners choose the land use that maximizes profit. Let π_{ik} be the profit per acre for landowner i associated with land use k, net of any conversion costs and excluding land rents. Land use k is chosen by i if:

$$\pi_{ik} \geq \pi_{il} \text{ for all } l \neq k \tag{1.5}$$

With competitive land markets, the land rents for i will equal the maximum profit, π_{ik}. Thus, by regressing land rents on measures of climate, it is possible to estimate the economic value of climate for landowners, which will implicitly account for any substitutions or adaptations that landowners undertake. Lacking precise data on land rents, Mendelsohn et al. (1994) and Schlenker et al. (2006) use data on farm value from the U.S. Census of Agriculture, noting that farmland value is equivalent to the present value of future land rents.

In this work, if we maintain the Ricardian assumption that landowners choose the profit-maximizing land use, then the dependent variable in Equation (1.2), y_{ik}, can be thought of as an indicator for k being the profit-maximizing land use for i. In other words, $y_{ik} = 1$ when Equation (1.5) holds. This means that the cross-sectional representation in Equation (1.2) can be thought of as a latent-variable model, where farm-level per-acre profit is the unobserved latent variable. Estimation of the model identifies the effect of climate on the probability of choosing land use k, which is itself equal to the probability that land use k is the profit-maximizing land use.

Now consider the long-differences specification of Equation (1.4) using the subsample of parcels with common land use, k, in the base period, t_0, as described in footnote 7. With the same latent-variable interpretation, Δy_{ik} represents an indicator for whether land use k continues to be profit-maximizing at time t_1. Notice that the value of Δy_{ik} does not provide information on whether profits have increased or decreased relative to time t_0. The Ricardian assumption only allows us to make statements about profits within a single year, e.g. "cultivated cropland is no longer the profit-maximizing land use for owner i at time t_1."

1.2.3 Identification in the Long-Differences Model

Burke and Emerick (2016) and Dell et al. (2014) describe several advantages to the long-differences model. First, to the extent that $\bar{\mathbf{W}}_i$ is a better representation of $\mathbf{C}$ than $\mathbf{W}_{it}$, the long-differences model is a closer approximation of the true structural model behind Equation (1.1) since the estimated impacts are identified from actual variation in climate rather than short-term weather. The long-differences model is also more likely to implicitly account for both adaptation and intensification effects while, like the panel model, not suffering from time-invariant omitted variables bias. Finally, observed changes in climate over the past 30 years are similar in magnitude to mid-century projections. All together, this suggests that long-differences estimates may be more appropriate for predicting impacts under projected climate change.

The identification assumption in the long-differences model of Equation (1.4) is similar to the common trends assumption in difference-in-differences models. The assumption is that conditional on $\Delta\bar{\mathbf{Z}}_i$ (if included), changes in land use at parcels within a region, r, would have been equal, on average, if not for changes in climate. In other words, the common trends assumption applies to units within r and is conditional on $\Delta\bar{\mathbf{Z}}_i$. The identification assumption will fail to hold if changes in unobserved local factors, captured by the error term $\Delta\bar{\epsilon}_{ik}$, are correlated with observed changes in climate.

In general, we do not want to control for local measures of profit associated with the different land uses. Although changes in profit will certainly affect land-use decisions (as demonstrated in Lubowski et al. (2006) and related studies), profit may also directly respond to changes in climate. Indeed, this is demonstrated in the previously mentioned Ricardian analysis. Thus, in the terminology of Angrist and Pischke (2009), profit is a "bad control."[8] Since this issue can be counterintuitive, we discuss it further in Appendix A.

Burke and Emerick (2016) discuss several threats to exogeneity when the dependent variable is agricultural yield. One main concern is local land use change, which could affect measured county yield (their dependent variable) and also be correlated with observed climate change. In contrast, our paper focuses directly on the question of whether changes in land use and climate change are correlated. Any effect of climate on underlying yield is subsumed into the reduced form land-use equation, as discussed above.

More important for our work, many studies have shown that land-use choices can have feedback effects on local and regional climate (Brown et al., 2014). Thus, it is fair to ask whether the observed changes in climate are causing adaptations in land use, or whether land use is changing for other reasons and leading to observed differences in climate. There are several reasons why we are not concerned about reverse causality.

First, there is some degree of uncertainty in climatology research about the magnitude of feedback effects as well as the exact pathways. For instance, Mueller et al. (2016)

[8] Dell et al. (2014) also discuss this issue and refer to the problem as "over-controlling" (p. 743).

suggest that intensification of cropland management practices, rather than conversion of land use per se, might better explain deviations in local climate. In terms of magnitude, estimates of the effect of land use conversion on local climate trends are, in general, small relative to observed changes in our data. Fall et al. (2010) estimate the effect of land use conversion on decadel deviations in trends between surface temperatures and reanalysis data. Conversions of agriculture to other uses result in deviations of 0 to $0.1°\mathrm{C}/10$yr, with varying levels of significance, while conversions of other uses to agriculture show a cooling effect between 0 and $-0.1°\mathrm{C}/10$yr. These changes are quite small relative to the distribution of changes in average temperature, as shown in Figure 1.3a and discussed more formally in Section 1.3.1, where many counties experience changes well above $+0.75°\mathrm{C}$.

Second, the land "points" used in the analysis represent relatively small land areas. As discussed in Section 1.3, our land-use data consist of a representative sample of land points that are anonymous at the county level. That is, we know which county each point belongs to, but we do not know where the point is located *within* the county. Therefore, we use county-level measures of observed climate as the explanatory variables of interest in our regressions. Of course, each "point" is surrounded by a parcel of land with similar characteristics. Yet the parcels containing each point are likely too small relative to the county as a whole for the land-use choice to directly affect the average climate measure for any county. While, we do not observe the size of parcels, the data contain sample weights that estimate the total county acres represented by the parcel, i.e., the total similar acreage that could potentially provide a climate feedback effect. On average, each point represents a meager 0.2% of total county acreage; points are unlikely to produce measurable feedback effects on their own.[9]

Still, if changes in land use are spatially correlated, then it is possible for collective feedback effects to impact the measures of climate change. However, the bottom half of Table 1.2 shows that the average county level change as a fraction of total county area is 5% or lower, in absolute value, for all land uses. This combined with the relatively low estimated feedback effects mentioned above lead us to conclude that reverse causality is not a primary concern for our analysis.

Another potential threat to exogeneity is time-varying agglomeration effects associated with the development of local upstream or downstream industry, i.e., local shocks to demand for products associated with a particular land use. Land use often involves some form of production, such as agriculture or forestry. Goods produced must be transported to market, or in the case of pasture or range, livestock might be transported to the parcel. In some

[9]The average number of points/parcels per county is 414 with 1^{st} and 99^{th} percentiles of 148 and 1,041, respectively. For county acreage shares, the same percentiles are 0.008% and 1.2%.

sense, developed land is no different since people will need to travel to and from homes and businesses. These types of input-output linkages can drive related industries to co-locate spatially in order to minimize transportation costs, a phenomenon called "coagglomeration" (Ellison et al., 2010). With land use, coagglomeration is unmistakable. Sawmills are located in or near forests, dairy farms are surrounded by alfalfa and other feed crops, and corn ethanol refineries are located in the Corn Belt (McWilliams and Moore, 2016a).

In our long-differences framework, coagglomeration could be a problem if there are shifts in input-output linkages involving land use that are also correlated with changes in climate. For example, if new sawmills locate in areas that also experience favorable climate shocks for forestry, then the impacts associated with unobserved changes in local demand will confound estimates of climate impacts. The use of state fixed effects should help mitigate these problems.

However, one caveat is in order. If changes in I-O links are also driven by climate (or by the changes in land use that are driven by climate), then we do not need to worry about omitted variables bias.[10] Our goal is to estimate casual, yet reduced form, impacts of climate change. We want the direct effect of climate on land use to be captured, but we are also interested in any other indirect effects that also result from the change in climate. If changes in climate also cause downstream industries to migrate, then we ideally want that effect to be captured as well. If, on the other hand, the changes in the I-O links are correlated with climate, but not *caused* by climate, then omitted variables bias would be a concern. This is particularly true if the changes are unlikely to be repeated as we extrapolate using mid-century climate projections. Intuitively, if climate impacts are not isolated from other correlated factors, then our projections will implicitly include a repeat of those same factors.

One example that we consider is the growth of the corn ethanol industry between 2002 and 2012. The Renewable Fuel Standard, born with the Energy Policy Act of 2005 and expanded with the Energy Independence and Security Act of 2007, mandates that a certain volume of ethanol be produced and blended with transportation fuel each year. Using data from McWilliams and Moore (2016a), there were 45 operating corn ethanol refineries in Midwest states in 2002 and only 2 refineries operating outside the region.[11] These refineries had a total production capacity of approximately 2.3 billion gallons per year (bgy). Between 2002 and 2012, 128 new ethanol refineries were constructed in the Midwest, and combined with upgrades at existing plants, total production capacity increased by 10.3 bgy

[10]This is closely related to our previous discussion of "bad control" with respect to including measures of profit as explanatory variables. See the Appendix for further discussion.

[11]Midwest states considered: IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD, and WI.

(441%). At a conversion rate of 2.8 ethanol gallons per bushel of corn and an average yield of 170 bushels per acre, the new facilities and upgrades would demand an additional 3.7 billion bushels (22 million acres) at full production capacity. Compare this to total US corn production of 8.7 billion bushels in 2002, which rose to 12.7 billion by 2007 according to U.S. Census of Agriculture data.[12]

McWilliams and Moore (2016a) find that crop choice responds locally to new ethanol production capacity, with the amount of land transitioning to corn decreasing as a function of distance from the refinery. If the location of new ethanol production capacity is correlated with changes in climate, then the effects of the biofuel boom will be confounded with our climate impacts estimates. Section 1.4.3 examines this question and concludes that observed changes in climate are not correlated with new ethanol production. In other words, there is reasonable variation in observed climate change within areas that also experienced increased ethanol production. Nonetheless, we include additional robustness checks in section 1.4.3 that estimate land-use changes over the period 1982-2002, ending before the major expansion of U.S. ethanol production. Results are broadly consistent with the estimates over the full period.

The ethanol expansion is one example of a time-varying agglomeration effect, and others may be worth considering. A variant on this theme is the intensification or shift of entire industries to specific regions for political or regulatory reasons such as the leniency of environmental regulation or tax incentives (e.g., the shift of the timber industry from the Pacific Northwest to the Southeast, or recent North-to-South migration trends). If these changes are correlated with changes in climate, then the estimated climate impacts will be biased. While there is no test to assure that the analysis is safe from this problem, we assume that our state fixed effects capture these sorts of regional trends. Furthermore, the point-level fixed effects account for all time-invariant properties of each point that make it better suited to particular land uses. Examples are field topology, altitude, soil texture and quality, and proximity to highways and navigable rivers. In general, we maintain the assumption, as in Burke and Emerick (2016), that observed climate change is "plausibly exogenous", which is also consistent with the wide range of work cited in Dell et al. (2014).

1.3 Land Use and Observed Climate Data

We obtain data on parcel level land-use transitions from the National Resources Inventory (NRI), a statistical survey of U.S. land-use conditions that is conducted by USDA's Natural

[12] Accessed 4/23/2016 using USDA NASS Quick Stats at https://quickstats.nass.usda.gov/.

Resources Conservation Service.[13] The modern NRI program was born following the Soil and Water Resources Conservation Act of 1977 and other related legislation that mandated recurrent appraisals of the inventory. Its purpose is to provide "updated information on the status, condition, and trends of land, soil, water, and related resources on the Nation's non-Federal lands" (U.S. Department of Agriculture, 2015).

The NRI survey process has evolved over the years with, for instance, recent surveys making use of modern remote sensing and geospatial data processing technologies. However, the underlying population of sample points has remained largely unchanged. The original 1982 survey points were selected using a two-stage stratified area sampling procedure, as described in Nusser and Goebel (1997).[14] These points have been tracked over time to form the longitudinal NRI dataset. In total, there are 1,362,936 points covering 1982-2012. This drops to 849,851 when we restrict to points East of the 100^{th} meridian that have never been federally owned.

The usefulness of the NRI data for this paper derives from its longitudinal nature. We are able to follow land-use choices and characteristics for the specific geospatial points at five year intervals between 1982-1997 and then annually from 2000-2012.[15] This allows us to examine land-use transitions that might otherwise be hidden in more aggregated data. Six broad land-use categories are analyzed: cultivated cropland, noncultivated cropland, pasture, range, forest, and developed. Transitions into and out of irrigated agriculture (all cropland and pasture that is irrigated) also are analyzed.

As discussed earlier, the data are subject to confidentiality restrictions; the exact locations of each sample point in our data are unknown below the county-level. For this reason, we are forced to aggregate our climate data to the county level as well. However, this may be desirable if it also alleviates concerns about feedback effects.[16]

Our climate variables are created using the weather data from Annan and Schlenker

[13] Although NRI data collection formally began in 1977, its roots can be traced to the 1934 National Erosion Reconnaissance Survey, the passage of the Soil Conservation Act of 1935, and the subsequent formation of the Soil Conservation Service (SCS) (U.S. Department of Agriculture, 2015). In its history, the SCS periodically tallied inventories of U.S. natural resources, such as with the Soil and Water Conservation Needs Inventories of 1945, 1958, and 1967. In 1994, the Soil Conservation Service became the Natural Resources Conservation Service.

[14] First, land was divided into strata, from which primary sampling units are selected. Next, the actual sample points were selected from within the chosen primary sampling units. For example, in areas with borders defined by the Public Land Survey System, there are typically 16 square townships per county, where each township is composed of 36 square-mile sections. Here, the NRI typically divided each township into three strata containing 12 sections each. From each stratum, two quarter-sections were selected as primary sampling units, from which three sample points were selected (Nusser and Goebel, 1997).

[15] Despite annual data covering 2000-2012, major data releases still conform to a 5-year cycle. Thus, 2002, 2007, and 2012 represent major releases of NRI data. We stick to these years in our analysis.

[16] See Section 1.2.3.

(2015), which is an updated edition of the data in Schlenker and Roberts (2009) and consists of high resolution (2.5 x 2.5 mile grid) daily temperature and precipitation data from 1950-2014. The new version extends the data from the original endpoint of 2005 and uses a reduced set of weather stations that are constant over the entire period. This guards against a potential problem where variation in measured weather could be due to changes in the set of operating weather stations over time rather than actual weather.

Consistent with Burke and Emerick (2016) and Dell et al. (2012), we construct our climate variables by averaging weather outcomes over a specified number of years.[17] The assumption is that these averages are able to capture longer-run changes in climate that are perceived by landowners. This is an approximation as the term "climate" is typically used to represent the full distribution of potential weather outcomes, and thus is not fully described by sample means. Still, average weather has been shown to be a powerful representation of climate in many studies, including Burke and Emerick (2016), which is why it remains as our focus.[18] A question that arises is: how many years of averaged weather data sufficiently represents climate? Burke and Emerick (2016) focus on a five-year average, which is sensible when the dependent variable is yield, but may be too short when considering broad land-use change. Our preferred specification uses ten-year averages, but we also present robustness checks with other lengths.

Following Snyder (1985), we derive our climate variables by first using a sine curve to interpolate the daily time spent in $1°$C-wide temperature bins between the given minimum and maximum temperatures for each grid cell. We then use these to construct county averages of the total amount of time spent in each bin, either annually or for a defined growing season. We also construct measures of total average precipitation by county, which simply requires summing the total annual (or growing season) precipitation for each cell and taking the county average.

Using the $1°$C-wide temperature bins, we construct two types of climate variables for our analysis. First, we aggregate to a set of $5°$C-wide bins, which we use as a set of nonparametric treatment variables, allowing each $5°$C-wide bin to have a different effect on land-use decisions. Second, following Burke and Emerick (2016) and Schlenker and Roberts (2009), we estimate land-use outcomes as piecewise linear functions of degree days. For instance, we set a lower bound equal to t_0 and a kink point equal to t_1. This allows degree days between t_0 and t_1 to have a different effect from degree days above t_1.

Formally, we construct degree days for the lower piece, DD_{t_0,t_1}, and the higher piece,

[17] Burke and Emerick (2016) use the original data from Schlenker and Roberts (2009) through 2005 to construct their climate variables.

[18] See Dell et al. (2014) for many other examples.

$DD_{t_1,\infty}$, using the set of 1°C-wide temperature bins as follows where f_i is the fraction of any given day spent in bin i with lower bound b and upper bound $b+1$,

$$DD_{t_0,t_1} = \begin{cases} 0 & b < t_0 \\ (b + 0.5 - t_0)\, f_i & t_0 \leq b < t_1 \\ t_1 - t_0 & b \geq t_1 \end{cases}$$

$$DD_{t_1,\infty} = \begin{cases} 0 & b < t_1 \\ (b + 0.5 - t_1)\, f_i & b \geq t_1 \end{cases} \tag{1.6}$$

The end result is a series of annual county-level averages for every year between 1950 and 2014 for all of the constructed measures (degree days, 5°C-wide bins, and total precipitation). Our main specifications take 10-year averages for 1973-1982 and 2001-2012, which we difference according to Equation (1.4).

1.3.1 Observed Land Use and Climate Changes between 1982-2012

Table 1.1 shows transitions between the broad land-use categories in the NRI between 1982 and 2012 for all non-federally owned land in the continental United States. During this period, total land in cultivated crops decreased by 64 million acres (-17%), noncultivated cropland increased by 8 million acres (+18%), pasture decreased by 9 million acres (-7%), range decreased by 10 million acres (-2%), forest increased by 6 million acres (+2%), and developed land increased by 42 million acres (+58%).[19] While these aggregate changes are significant, they mask even greater turnover at the parcel level. Other than CRP, which was not in existence in 1982, land uses with the highest percentage of new acreage since 1982 are noncultivated cropland (66%), pasture (38%), and developed land (38%). For

[19] Cultivated cropland: land that is in row crops or other close-grown crops and may include hayland or pastureland that is in rotation with cultivated crops. Noncultivated cropland: permanent hayland and horticultural cropland. Pasture: vegetative cover of grasses, legumes, and/or forbs, or other forage plants that is managed principally for livestock grazing. Range: includes grasslands, savannas, tundra, and some wetlands and deserts; plant cover is primarily native grasses, grasslike plants, shrubs or forbs, or introduced forage species that are managed like traditional rangeland; practices such as deferred grazing, burning, chaining, and rotational grazing may be used, but fertilizer and chemicals are generally not applied. Forest: U.S. Department of Agriculture (2015) defines forest as land that is "at least 10 percent stocked by single-stemmed woody species of any size that will be at least 4 meters (13 feet) tall at maturity. Also included is land bearing evidence of natural regeneration of tree cover (cut over forest or abandoned farmland) and not currently developed for non-forest use. Ten percent stocked, when viewed from a vertical direction, equates to an areal canopy cover of leaves and branches of 25 percent or greater. The minimum area for classification as forestland is 1 acre, and the area must be at least 100 feet wide." Developed: also from U.S. Department of Agriculture (2015), the "developed land category includes (a) large tracts of urban and built-up land; (b) small tracts of built-up land of less than 10 acres; and (c) land outside of these built-up areas that is in a rural transportation corridor (roads, railroads, and associated rights-of-way)." CRP: land enrolled in the Conservation Reserve Program.

cultivated cropland, 11% of 2012 acreage was new since 1982. The uses with the highest percentage of land that switched to another use between 1982 and 2012 are noncultivated cropland (60%), pasture (43%), and cultivated cropland (26%).

Figures 1.1 and 1.2 map acreage changes that have been aggregated to the county level for the seven major land uses as well as for irrigated land, which is discussed in section 1.4.4. In all cases, there is spatial correlation in both the direction and magnitude of change. This suggests that local factors, such as changes in climate or demand, may be driving the changes. A possible exception is developed land, which has seen small increases in most counties with larger changes occurring around existing urban areas. As shown in Table 1.2, the average change as a percentage of total county area is small for all land uses ($\leq 5\%$ in absolute value), although there are also some outliers.

Figures 1.3 and 1.4 show the distribution of county-level observed climate change over the period 1982-2012, where climate is represented by 10-year averages calculated over the full calendar year (Jan-Dec). The temperature variables are all skewed to the right. Some counties have experienced slight cooling, while others have warmed by over $1°\mathrm{C}$ (Panel 1.3a). Panels 1.4a-1.4d show that exposure to temperatures over $25°\mathrm{C}$ has generally increased. To put these changes in perspective, Burke and Emerick (2016) estimate that each additional degree day above $29°\mathrm{C}$ reduces corn yield by 0.44%. Panel 1.3d shows that some counties experienced changes of over +40 degree days above $30°\mathrm{C}$; the average is just over +6 degree days. Changes in precipitation also appear to be slightly skewed to the right, although many counties have experienced decreases in average precipitation.

These changes are depicted spatially in Figures 1.5 and 1.6. There is spatial correlation in observed changes for all of the climate measures. However, there also appears to be variation in these changes within many states. Since state fixed effects are used in the regressions to capture regional trends, it is important that there be adequate variation in climate change within states that is not simply measurement error (Fisher et al., 2012). Table 1.3 examines how much variation remains in our climate measures after controlling for state fixed effects. Using Fisher et al. (2012) as a guide, we estimate regressions of each climate measure on: (1) a constant only, and (2) a constant plus the set of state fixed effects. The standard deviation of the residuals from any regression is a measure of the remaining variation in the climate variable. For comparison, the exercise is performed for both the observed climate measures from 1982 (climate levels) and the actual climate change variables that are used in the analysis. The table shows that state fixed effects absorb almost 70% of the variation in many of the 1982 level measures, while the long-differenced versions lose between 30 and 40%, on average. With state fixed effects, substantial climate variation is preserved with the long-differenced climate change variables.

1.4 The Effect of Climate Change on Land-Use Adaptation

We begin this section with preliminary analysis that motivates our restriction to non-irrigated NRI points east of the 100^{th} meridian. We then describe the main results on land-use adaptation to climate change over 1982 to 2012. We next demonstrate the robustness of our estimates by using climate variables constructed from varying lengths of average weather as well as alternate end years for the long-difference calculations.

In all cases, we estimate linear probability models (LPMs) since our dependent variables represent binary decisions by landowners.[20] We include a constant and state fixed effects in all specifications, which allow states to have different intercepts.[21] In addition, we allow positive changes in precipitation to have a different effect from negative changes in precipitation. Although not shown, our results are robust to other specifications of the precipitation effect.[22] We estimate every regression twice using two different specifications of the temperature variables: once with the $5°\mathrm{C}$-wide time exposure bins, and once with the piecewise linear degree day variables. For the piecewise linear degree days, we set the kink point at $30°\mathrm{C}$ for all regressions. To choose this point, we focused on the LPM regression estimating the probability that cultivated cropland points in 1982 remained in cultivated cropland in 2012. Similar to Burke and Emerick (2016), we looped over regressions with the kink point set at every integer between 11 and 39. The regression with a kink point of $30°\mathrm{C}$ resulted in the lowest estimated residual sum of squares. This matches the results of Burke and Emerick (2016) closely, as they found an optimal kink point of $29°\mathrm{C}$ for corn yield.

1.4.1 Preliminary Analysis: East vs West

The preliminary analysis focuses on the question of whether models should be estimated using NRI points from all counties in the continental United States or only counties in the

[20] We have also performed robustness checks using simple logit and probit models, which are consistent with our main findings. We focus on the linear probability model because it has several advantages over nonlinear models. In particular, causal analysis remains valid with exogenous treatment variables while also not requiring functional form assumptions about the error term. See Angrist and Pischke (2009).

[21] State specific intercepts result from the differencing of state specific trends in the original panel specification.

[22] We have tested models with a single linear precipitation term, interactions of changes in average precipitation with changes in average temperature (in bins or piecewise linear degree days), and with squared precipitation terms. We prefer the specification with separate effects for positive and negative changes because (1) results are similar across all specifications, (2) the terms provide flexibility in landowner response to drought versus precipitation increases, and (3) the specification is sufficiently parsimonious for nested logit models to converge (this research is still in progress).

East. Schlenker et al. (2005) discuss the fundamental differences within the U.S. between the largely irrigated West and the non-irrigated East. They point out that in irrigated areas, precipitation does not adequately represent the true water supply as it does in rainfed areas. As they put it, "irrigation breaks the link between the growth of a plant and the climate at the farm where the plant is grown" (p.396). For this reason, many subsequent studies have focused exclusively on climate impacts in counties east of the 100^{th} meridian, which is typically seen as the boundary beyond which (to the west) farming increasingly requires irrigation (Schlenker et al., 2006).[23]

In our model, the implicit assumption is that a given change in precipitation or time spent in a temperature interval will have the same effect across all states in the estimation sample. Table 1.4 examines whether this is a sensible assumption when estimating the probability of cultivated cropland not switching land uses between 1982 and 2012. Columns (1) and (2) use the entire NRI sample in the continental U.S.; columns (3) and (4) restrict to points that were not irrigated in 1982; columns (5) and (6) consider non-irrigated points east of the 100^{th} meridian, while (7) and (8) restrict to non-irrigated points in the West. A first observation is that coefficient signs, magnitudes, and significance are very similar between all of the entire-U.S. and East-only estimates. However, there are important differences when we compare the East- and West-only results. In particular, the effect of extreme heat days above $35°\mathrm{C}$ (or the upper degree day (DD) piece) has opposite signs in the two regions. In addition, the effect of precipitation varies as well. Negative changes in precipitation reduce the probability of staying with cropland in the West, but have a much smaller (and insignificant) effect in the East. On the other hand, positive precipitation changes make cropland in the East more likely not to switch and, paradoxically, make cropland more likely to switch in the West. These results suggest that the East and West are not good controls for each other. Even restricting to non-irrigated points, farms in the arid West respond differently to temperature and precipitation changes than farms in the East. Therefore, in our remaining analysis (except for the analysis of irrigation in agriculture), we follow the recent literature and focus exclusively on non-irrigated NRI points in counties east of the 100^{th} meridian.[24]

1.4.2 Main Results

Our main results cover a series of LPMs that begin with NRI points in a given land use in 1982 and estimate the probability of those points transitioning to one of the following

[23] See, e.g., Schlenker et al. (2006), Schlenker and Roberts (2006), Schlenker and Roberts (2009), Annan and Schlenker (2015), and Burke and Emerick (2016).

[24] Specifically, we use counties whose centroids are east of the 100^{th} meridian.

land uses in 2012: cultivated cropland, noncultivated cropland, pasture, range, forest, or developed land. We cycle through each of these land uses as the starting use in 1982, except for developed land since it rarely switches to another use. Tables 1.5-1.9 present estimates of these regressions using the time exposure bins, while Tables 1.10-1.14 use the piecewise linear degree days. Tables 1.15 and 1.16 present a different analysis where we estimate the probability of switching into a given land use in 2012 (given by the column) from all other land uses combined. Taken together, these tables allow us to compare the effect of climate change on a range of potential land-use outcomes.[25] In general, we focus discussion on the results using the time exposure bins as it allows more subtlety in capturing effects across the different land uses. We note that the results with the piecewise linear degree days are broadly consistent, and also note that the piecewise linear form is useful when estimating models of multinomial choice, such as nested logit, where it can be difficult to achieve convergence with models containing many variables.

We begin with results related to cultivated cropland, in part due to the perspective provided by Schlenker and Roberts (2009) and Burke and Emerick (2016) on the response of crop yields to temperature and climate change. Those studies demonstrate that exposure to temperatures of approximately $29°\mathrm{C}$ and lower is beneficial for plant growth, while exposure to temperatures above $29°\mathrm{C}$ is increasingly harmful. Since farm profit is directly linked to yield, one might expect these same thresholds to be important for land-use decisions. Indeed, our results suggest that they are. Temperature changes in the [25, 30) bin lead to a higher probability of land staying in cultivated cropland (column 1 of Table 1.5); an additional day between 25 and $30°\mathrm{C}$ increases the probability of not switching by 2.64 percent. In addition, these same temperature changes increase the probabilities of transitioning to cultivated cropland from pasture and forestland (column 1 in Tables 1.7 and 1.9, both of which are major land-use categories).[26] Table 1.15 shows a similar result when we group all the other land uses together and assess the probability of switching into cultivated cropland; the estimated coefficient is positive and significant for changes in the [25, 30) bin. Farmers thus are responding to favorable changes in temperature by either keeping land in cultivated cropland or reallocating land to cultivated cropland.

[25] Note that Tables 1.5-1.14 each use a distinct subsample from the population of non-irrigated NRI points east of the of the 100^{th} meridian, and that sample is constant for all columns in a given table. If the land use choices given by the columns were exhaustive, then one would expect the sum of the estimated coefficients in any given row to be zero as the marginal effect of an additional day between 30 and $35°\mathrm{C}$, for example, would be distributed across the possible choices. With separate OLS regressions, this is not a guaranteed outcome, which is one reason that we continue to work on extensions to models of multinomial choice, such as the nested logit.

[26] These results on switching into cultivated cropland are important since the other base land uses apply different subsamples of the NRI dataset. The different subsamples make the results a form of robustness check on the results for cultivated cropland as the base use.

Farmers similarly are responding to harmfully high temperature changes by either removing land from (i.e., not staying in) cultivated cropland or not reallocating land to cultivated cropland. An additional day between 30 and $35°\mathrm{C}$ decreases the probability of staying in cultivated cropland by 0.84 percent, while an additional day of extreme heat above $35°\mathrm{C}$ decreases the same probability by a substantial 4.22 percent (column 1 of Table 1.5). Temperature changes in the [30, 35) bin also decrease the probability of switching into cultivated cropland from the base land uses of pasture and forest (column 1 in Tables 1.7 and 1.9). One exception to this pattern occurs with rangeland (Table 1.8), in which an additional day in the [30,35) bin increases the probability of switching to cultivated cropland, although an extra day of extreme heat above $35°\mathrm{C}$ reduces the same probability. Table 1.15 generally reflects this broad pattern when we group all the other land uses together and assess the probability of switching into cultivated cropland; the estimated coefficients are negative and highly significant for changes in the [30, 35) bin and in the above $35°\mathrm{C}$ bin.

A third set of results relates to the relatively cool temperature bins of [15, 20) and [20, 25). Temperature changes in these bins show negative effects on cultivated cropland. They moderately decrease the probability of staying in cultivated cropland, and they decrease the probability of switching to cultivated cropland from pasture, forest, and (to a degree) noncultivated cropland. Incongruously, they increase the probability of switching from rangeland. Schlenker and Roberts (2009) find that corn, soybeans, and cotton yields show a U-shaped response between 15 and $25°\mathrm{C}$, i.e., our results are broadly consistent with the temperature effects on crop yields.

Turning from temperature to precipitation, we find that increases in total precipitation make cultivated cropland relatively more likely than the other choices: an additional cm increases the probability of continuing with cropland by 0.28 percent. The positive effect makes sense given the context of rainfed farming. Decreases in precipitation also have the expected sign, i.e., a negative change times a positive coefficient results in a decrease in the probability of staying in cultivated cropland, but the effect is relatively small and not statistically significant. The precipitation variables show little effect in explaining transitions from the other land uses to cultivated cropland.

For the other five land-use categories, we focus on Tables 1.6- 1.9 and Table 1.15.

The temperature changes show little effect on NRI points in noncultivated cropland in 1982 (column (2) of 1.6). The only significant effect occurs in the [10 15) bin, in which an additional day in the range increases the probability of staying in noncultivated cropland by 2.16 percent. In contrast, several of the temperature-change bins show a negative effect on converting from another land use to noncultivated cropland (column (2) of Table 1.15). This category includes both permanent hayland and specialty crops such as fruit and nut trees and vegetables. Set-up costs are substantial with specialty crops, thus it appears that the temperature changes were not sufficiently favorable for their production to cause a switch. A positive shock to precipitation decreased the probability of either staying in or converting to noncultivated cropland.

Pasture shows response to some of the temperature shocks. Temperature increases in the [25, 30) bin substantially decrease the probability of staying in pasture (column (3) of 1.7). Some of this can be explained by conversion from pasture to cultivated cropland. Increases in the [30, 35) bin similarly decreased the probability of staying in pasture. In addition, temperature increases in the [25, 30) bin and the [20, 25) bin decreased the probability of converting from another land use to pasture (column (3) of Table 1.15). Negative shocks to precipitation showed consistency in increasing the probability of staying in pasture and, as well, converting to pasture.

Rangeland is an interesting land-use category that covers a broad array of ecosystems, including grasslands, savannas, wetlands, deserts, and tundra (U.S. Department of Agriculture, 2015). There has been much recent research and commentary on the conversion of grasslands to agriculture, particularly due to the increased demand for biofuels.[27] Column (4) of Table 1.8 shows that four of the temperature shocks decrease the probability of staying in rangeland. Similarly, three of the temperature shocks decrease the probability of converting from another land use to rangeland (column (4) of Table 1.15), while only one shock increases the probability of converting. These temperature changes as a source of climate change thus appear to have reduced the relative profitability of rangeland.

Forestland shows response to the temperature shocks in the relatively high range of temperatures. Temperature increases in the [30, 35) bin substantially decrease the probability of staying in forest (column (5) of 1.9), while temperature increases above 35°C substantially increase the probability. These two effects also hold when considering the probability of switching from other land uses into forestland (column (5) of Table 1.8). Land conversion to developed land may explain the results for the [30, 35) bin. Above 35°C, this could be cultivated cropland being abandoned. As described in U.S. Department of Agriculture (2015) and footnote 19, land may be classified as forest if there are indications of "natural regeneration of tree cover (cut over forest or abandoned farmland) and not currently developed for non-forest use." Areas that experience changes in climate that are less favorable for agriculture or other uses may be left for "natural regeneration."

Developed land, like forestland, shows response to the temperature shocks in the relatively high range of temperatures. Temperature increases in the [30, 35) bin substantially increase the probability of switching to developed land from each of the other five cate-

[27] See, for example, Wright and Wimberly (2013).

gories. In contrast, temperature increases above $35°C$ substantially decrease the probability of switching to developed from pasture and forestland. These results are observed in column (6) in Tables 1.5-1.9. As mentioned above, we do not estimate regressions with developed land as a base use as developed land is largely irreversible, i.e., we do not observe conversions out of this category.

Although we have focused our discussion mostly on temperature effects, there are interesting precipitation effects as well. For instance, the regressions for noncultivated cropland in columns (1) and (2) of Table 1.6 show that increases in precipitation increase the probability of noncultivated cropland switching to cultivated cropland. These results are mirrored in column (2) of Table 1.5, which shows that cultivated cropland is more likely to switch to noncultivated cropland when precipitation decreases (i.e. drought) and less likely to make the conversion when precipitation increases. The same result holds for conversions from cultivated cropland to pasture (column (3) of Table 1.5), though the effect of precipitation on conversions from pasture to cropland is not meaningful or significant.

Table 1.15 shows that when we estimate the probability of switching from all other uses combined, increases in precipitation have a positive and significant effect on both cultivated cropland and developed land, while decreases in precipitation increase the probability of switching to range. However, except for developed land, these effects are not large, especially when we consider that the distribution of precipitation changes from 1982-2012 was mostly between -15 and 15 cm, as shown in Figure 1.3b. For instance, column (1) of Table 1.15 suggests that an increase in precipitation of 10 cm leads to an increase in the probability of conversion to cultivated cropland from all other categories of 0.4 percent. The effects of precipitation change in the "not-switching" regressions, in contrast, tends to be higher by an order of magnitude. Still, these precipitation effects are generally dominated by the temperature effects.

1.4.3 Robustness Checks

We perform several checks to determine whether the effects that we identified are robust. Rather than reproduce the many tables that we discussed in the previous section, we focus on the LPM for cultivated cropland in column (1) of Table 1.5 as this model is closely tied to recent research and provides intuitive results. However, the robustness of our results also carries over broadly to the results for the other land categories.

First, we check to see whether the results have something to do with 2012 being the end year for the analysis. Table 1.17 compares the estimates from long-differences models with 2002, 2007, and 2012 as end years. The estimates are very similar over the 20-25, 25-

30, and 30-to-35°C intervals. For the above-35°C range, 2007 and 2012 are very similar while the effect for 2002 is closer to zero and not significant. However, this is likely due to the lower frequency of exposure in the above-35°C range in 2002 compared to 2012. There is some variation in the precipitation effects between the years. First, the estimated effect of positive precipitation changes in 2002 has an unexpected negative sign, although it is not significant in the time exposure regression. The effect of negative changes has the expected sign for every year, but the effect diminishes from 2002 to 2012. In general, by 2012, exposure to extreme heat appears to be more important for switching out of cropland than drought. However, in all years, exposure in the 25-30°C range has a strong positive effect.

Next, we examine how the results change when the climate measures are constructed using average weather calculated from varying lengths of time (Table 1.18). In general, there is broad agreement between estimates using 10-, 15-, and 20-year averages, although there is again some variation in the precipitation effects. The 5-year estimates, on the other hand, seem out of place with unexpected signs on the precipitation variables as well as the 25-30 and 30-35°C ranges, although those effects are not significant. In some sense, the results for the 5-year estimates are not surprising as we expect land-use change to respond to changes in climate defined over longer periods of time. Still, we are encouraged by the similarity of the results for 10-, 15-, and 20-year averages.

As a final robustness check, we examine the potentially confounding ethanol boom of the last decade. If changes in local corn demand by ethanol refineries are correlated with changes in climate, then we may generate biased estimates of climate impacts. To examine this question, we use spatially detailed data on ethanol production capacity between 2002 and 2012 to see whether changes in capacity at the county level are correlated with our measures of climate change. We estimate regressions using three different subsamples of U.S. counties. First, we consider the same eastern counties as our LPM land-use regressions. However, this sample includes many counties outside of the corn belt that would be unexpected to build ethanol refineries. For this reason we also consider a sample that is further restricted to eastern counties in the Upper Midwest, as well as a sample that only considers eastern counties in the Upper Midwest that already had ethanol production capacity in 2002, a total of 42 counties.[28] Columns (1)-(3) of Table 1.19 present these results. The only significant results are for the 20-25°C range, which are positive, indicating that increases in county-level ethanol production capacity are correlated with increased exposure in that range. However, this is a range that is associated with negative changes in the probability of remaining in cultivated cropland, so these results appear not to gener-

[28]Upper Midwest states included: IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, and WI.

ate evidence of problematic bias. Columns (4) and (5) of the same table examine whether changes in climate are correlated with counties where at least one new refinery was built between 2002 and 2012. Here we see a positive significant result for positive changes in precipitation such that counties with increases in precipitation were also more likely to get a new plant. Since we also estimated that positive changes in precipitation increase the probability that cultivated cropland does not switch, it is possible that new plants could be driving these results. However, we believe this is unlikely for several reasons. First, as shown in Table 1.17, the precipitation effect diminished from 2007 to 2012. Second, we believe that ethanol capacity is more likely to be the factor driving local demand, and those specifications do not find significant results. Finally, since the heat exposure variables, as opposed to precipitation, appear to be the main drivers for cultivated cropland, we conclude that the ethanol boom is unlikely to be a confounder.

1.4.4 Irrigation

As a final analysis, we examine whether observed climate change has impacted the adoption or abandonment of irrigation in the United States. Using the NRI data, total irrigated land was relatively unchanged between 1982 and 2012 at just over 66 million acres. However, this again masks significant turnover at the parcel level, as we saw previously with the other aspects of land use. In the West, there were 43 million acres of irrigated land in 1982, which fell to 38 million by 2012. Behind these numbers, there were 6 million new acres of irrigated land and 11 million acres that switched away from irrigation. In the East, irrigation grew from 23 to 28 million acres, with 12 million acres of new irrigated land and 7 million acres that had left by 2012. Figure 1.2d maps these changes.

We estimate a series of linear probability models that estimate the effect of climate change on the probability of switching to irrigation (Table 1.20), as well as the probability of abandoning irrigation (Table 1.21), with separate regressions for NRI points east and west of the 100^{th} meridian. These regressions use the same set of explanatory variables as our previous land-use regressions, including state fixed effects. Standard errors are again clustered at the county level.

Looking at the probability of new irrigation, we see that the impact of heat in the East is very similar to the LPM estimates previously discussed for the probability of cultivated cropland not switching. Points are more likely to adopt irrigation with temperature changes that are also favorable to growing crops. However, the precipitation effects are the opposite sign of the previous results, which makes sense. Increases in precipitation should decrease the probability of new irrigation, while decreases in precipitation should increase the probability. These effects are statistically significant.

In the West, the precipitation effects have the expected sign, but are not significant. Instead, we see a significant positive effect for increases in exposure within the 30-35°C range. We again see a strong negative effect of extreme heat above 35°C, which suggests that irrigation is not enough to counter damages from high heat. Turning to column (5) of Table 1.21, we see that the same high heat interval also increases the probability of irrigation abandonment in the West. Perhaps landowners that experience such increases find it worthwhile to switch out of agriculture entirely. A similar effect is observed for negative changes in precipitation, which appear to also lead western farms to abandon irrigation. Combined with falling water levels, drought and high heat may be driving this transition. On the other hand, points that experience positive precipitation changes are also more likely to abandon irrigation, presumably due to an increased natural water supply.

In the East, precipitation changes do not appear to be driving the decision to stop irrigating. The coefficients have the same sign as in the West, but are much smaller and not significant. There is some evidence that increased exposure to heat above 30°C increases the probability of leaving irrigation, although the effects are not strongly significant. Instead, we see a more defined effect on exposure to cooler temperatures in the 15-to-25°C range. This could be explained by cooler temperatures causing less heat stress, reducing the benefit of irrigation. It could also be explained by cooler temperatures making agriculture, in general, less profitable, leading farms to exit entirely. More research is required to examine these effects.

1.5 Conclusion

This paper analyzes land-use change as a mechanism of adaptation to climate change. We apply high-quality land-use data from the National Resources Inventory to understand how temperature and precipitation shocks from 1982 to 2012 affect the probability of land-use change over six broad categories: cultivated cropland, noncultivated cropland, pasture, range, forest, and developed land. The main results show that landowners adjust land use in reasonable ways in response to the temperature and precipitation shocks. In particular, the results on cultivated cropland are strongly consistent with previous research by Burke and Emerick (2016) and Schlenker and Roberts (2009) on the impact of climate change and weather on U.S. crop yields. Producers are more likely to remain in, or switch into, cultivated cropland with temperature shocks in the 25-30°C range. They are more likely to switch out of, or not switch into, cultivated cropland with increased exposure to extreme heat, i.e., temperature shocks in the 30-35°C range and shocks in excess of 35°C. Producers are also more likely to switch out of, or not switch into, cultivated cropland with temperature shocks in the 15-20°C range and the 20-25°C range, although more work is required to determine whether these changes have been identified from cooling during the growing season, or warming in the non-growing season. Collectively, the results are robust to alternate methods of measuring climate change and shorter definitions of the study period. Lastly, the results are robust to a threat on exogeneity from the rapid expansion in corn ethanol production.

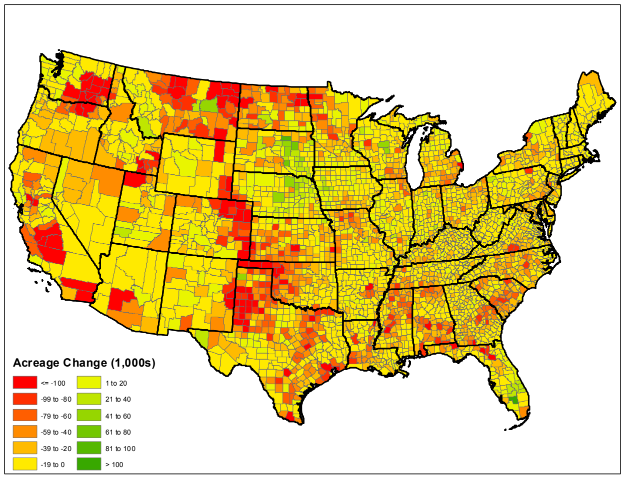
Developed land is an interesting case given that we do not observe conversions out of this category, i.e., its use is largely irreversible. A key finding here is that temperature increases in the 30-35°C range substantially increase the probability of switching to developed land from each of the other five categories. Newly developed land, in many cases, is driven by migration within, or immigration to, the United States. We intend to investigate migration using the long-differences methodology as a complement to this work on developed land. A certain consonance in findings seems likely when examining the climate-change effects on both migration and developed land.

This paper also analyzes whether climate change has impacted irrigation decisions in agriculture, in this case using data for both the East and West. Our results suggest that different factors have been important in the two regions. This is, perhaps, not surprising since they experienced opposite trends over the sample period; in the East, irrigated land increased by roughly 5 million acres, while irrigated land in the West decreased by about the same amount. In the East, irrigation is more likely to be adopted in areas where the temperature distribution has changed favorably for agriculture, but also where precipitation has fallen. However, the probability of irrigation abandonment does not respond strongly to precipitation changes in the East and appears to be driven primarily by increased exposure in the [15,20) and [20,25) temperature ranges. In contrast, abandonment responds strongly to precipitation changes in the West, but adoption is driven more by changes in heat.

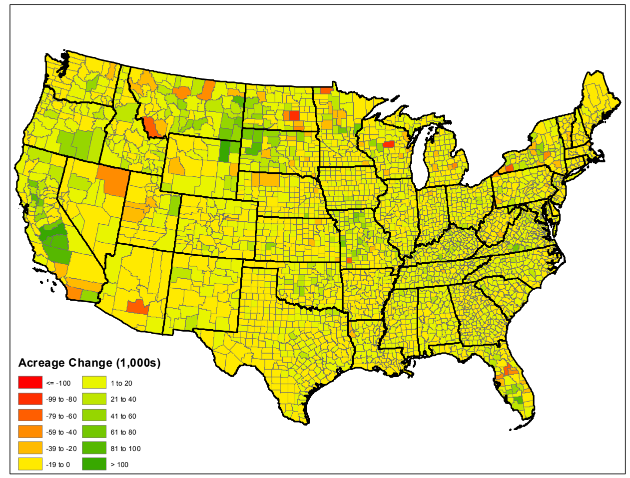
Taken all together, these results suggest that landowners will respond in similar ways to projected climate change over the next several decades. We are currently working to extend the long-differences idea to models of multinomial choice, which can be combined with climate projections to produce probabilities of expected land-use change that are guaranteed to remain in the [0,1] interval. The nested logit is one such model that has been used extensively with NRI data (see, e.g., Lubowski et al. (2006)). Our initial experiments with this model have been promising.

Figure 1.1: NRI Cropland, Pasture, and Range Changes, 1982-2012 (Thousands of Acres)

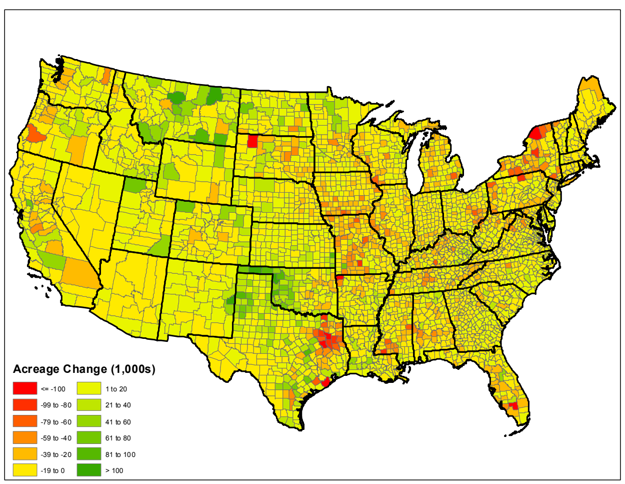
(a) Cultivated Cropland



(b) Noncultivated Cropland



(c) Pasture



(d) Range

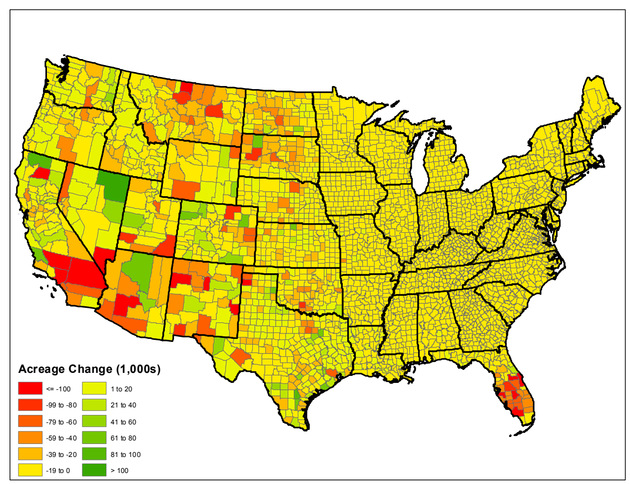
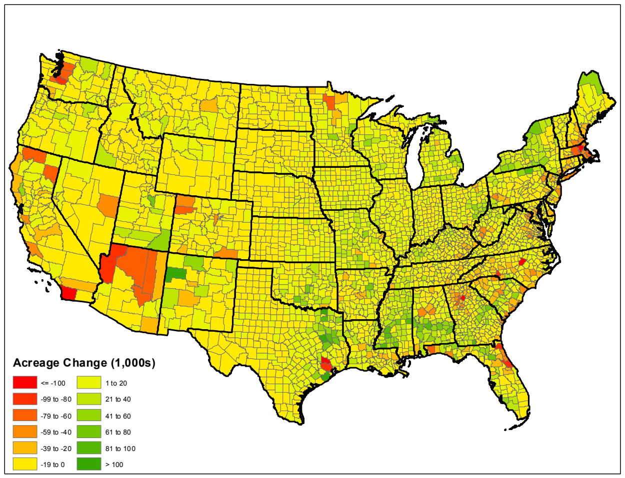
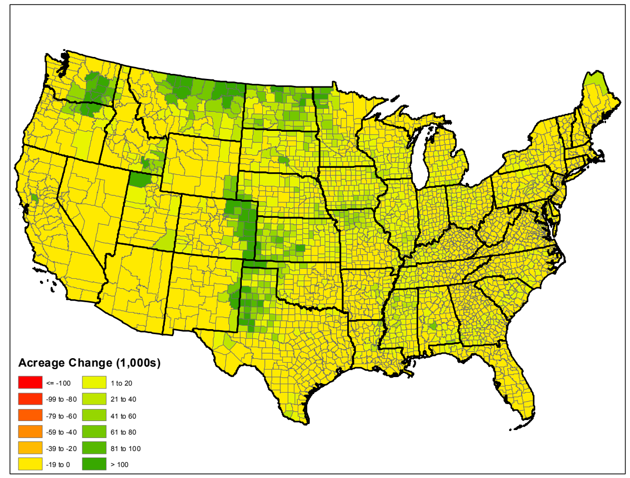


Figure 1.2: NRI Forest, CRP, Developed Land, and Irrigation Changes, 1982-2012 (Thousands of Acres)

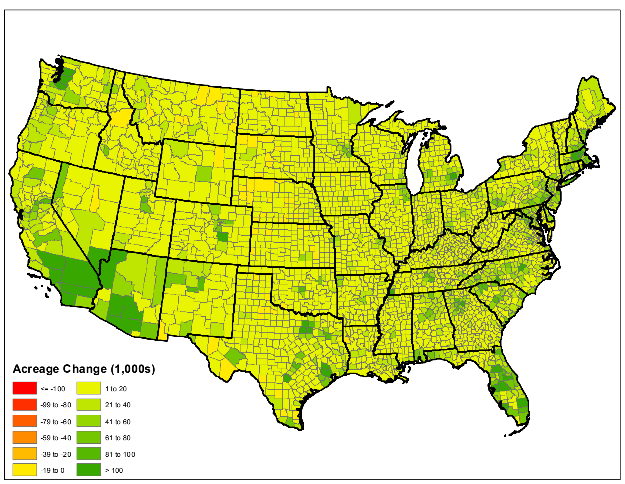
(a) Forest



(b) Conservation Reserve Program



(c) Developed



(d) Irrigated Land

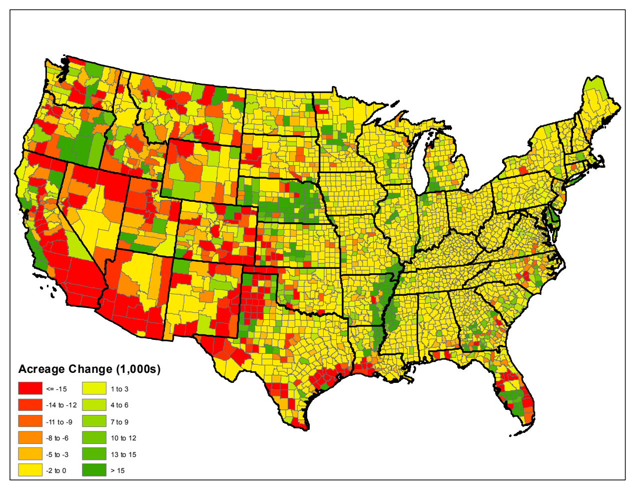
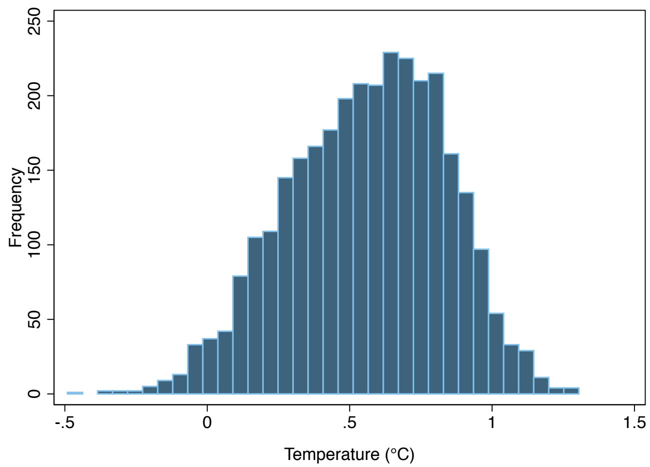
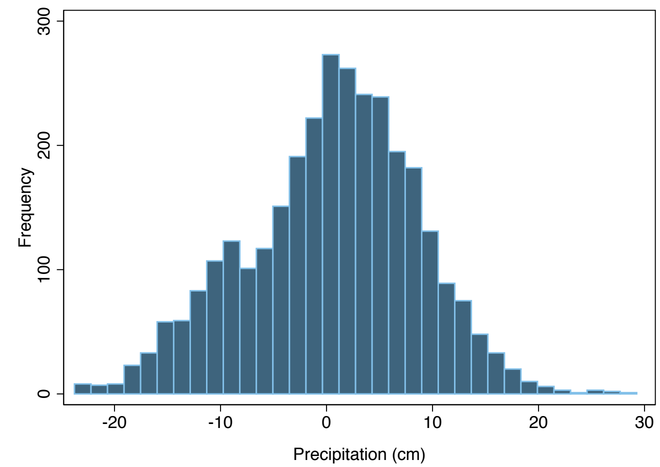


Figure 1.3: Changes in Average Temperature, Precipitation, and Degree Days, 1982-2012 (Differences in 10-year, Jan-Dec Averages)

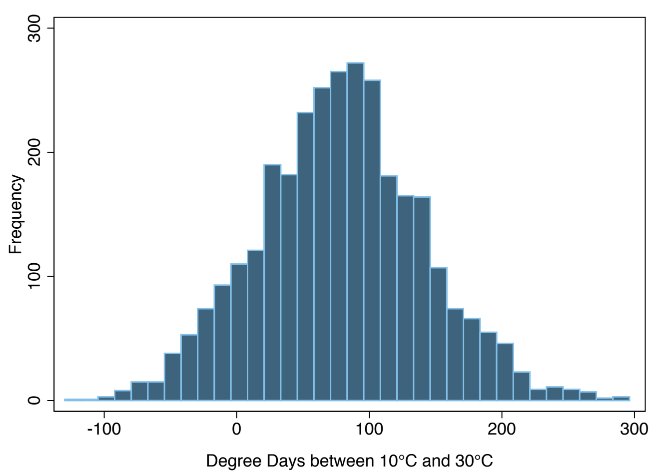
(a) Change in Avg Temperature (°C)



(b) Change in Avg Precipitation (cm)



(c) Change in Avg Degree Days Between 10°C and 30°C



(d) Change in Avg Degree Days Above 30°C

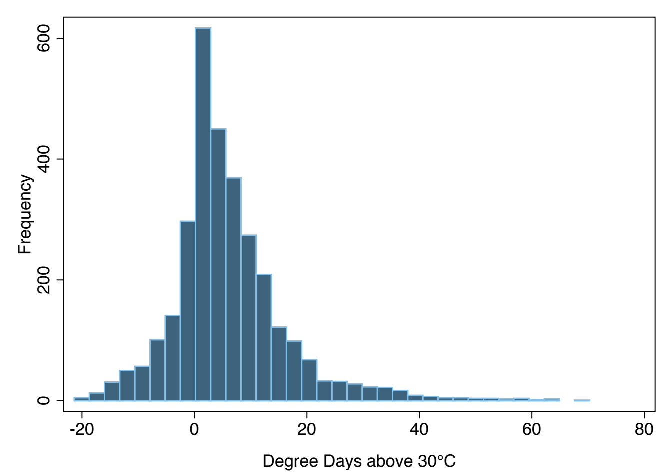
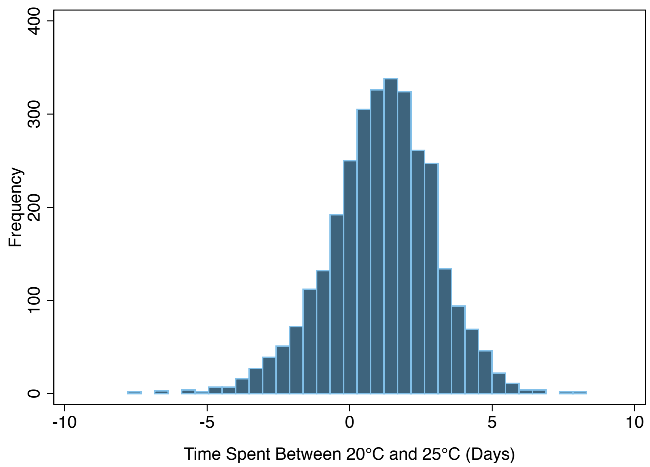
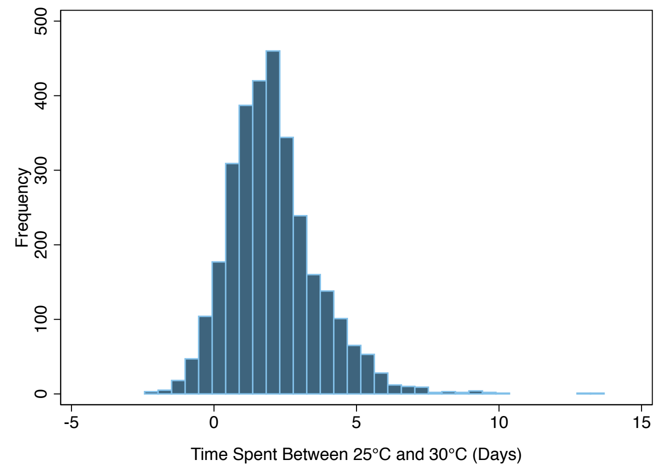


Figure 1.4: Changes in Temperature Exposure, 1982-2012 (Differences in 10-year, Jan-Dec Averages)

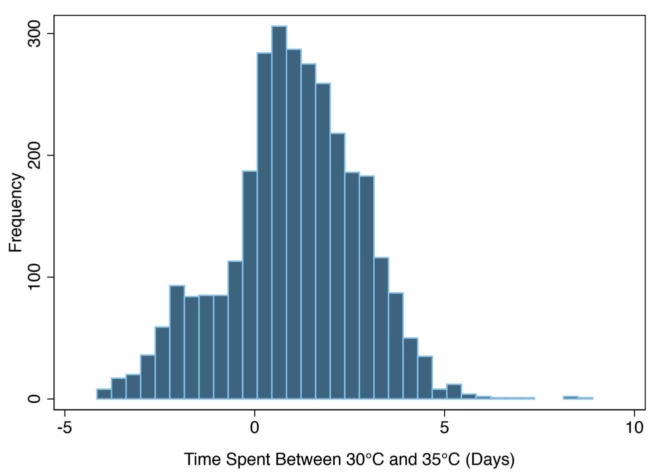
(a) Change in Avg Days Between 20°C and 25°C



(b) Change in Avg Days Between 25°C and 30°C



(c) Change in Avg Days Between 30°C and 35°C



(d) Change in Avg Days Above 35°C

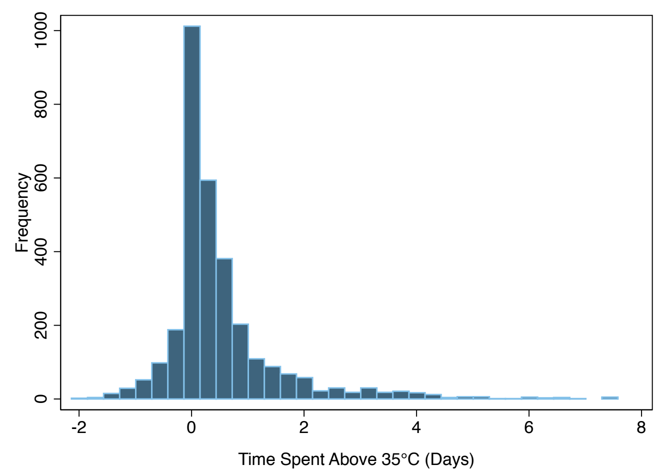
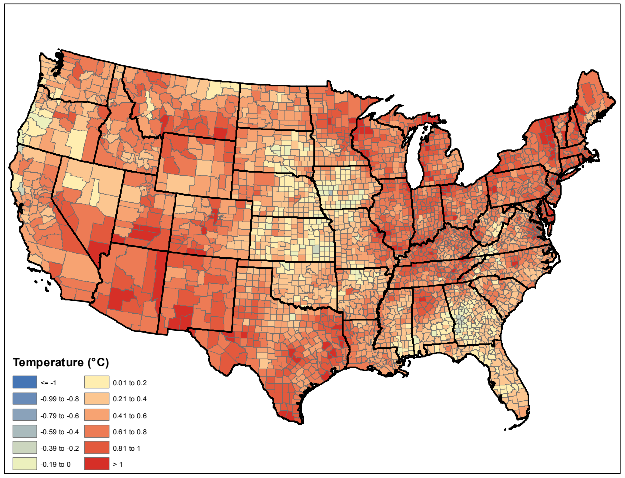
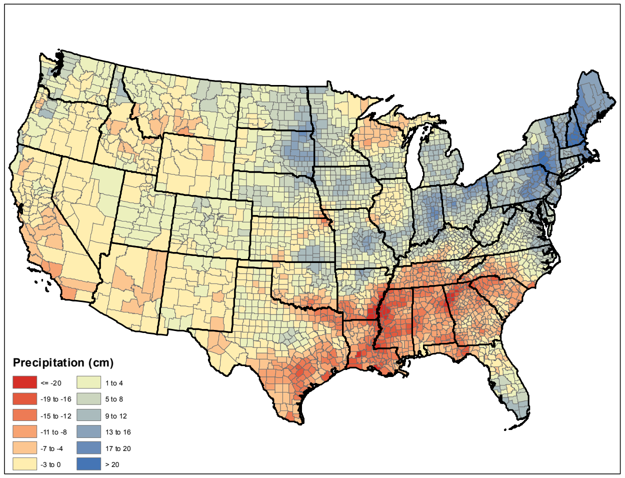


Figure 1.5: Maps of Changes in Average Temperature, Precipitation, and Degree Days, 1982-2012 (All Months)

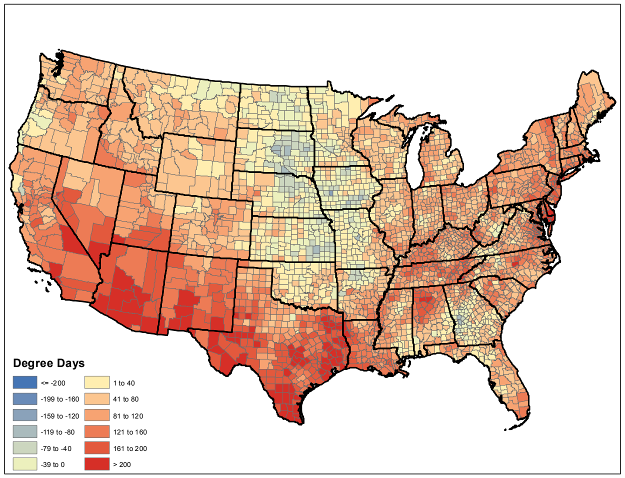
(a) Change in Avg Temperature (°C)



(b) Change in Avg Precipitation (cm)



(c) Change in Avg Degree Days Between 10°C and 30°C



(d) Change in Avg Degree Days Above 30°C

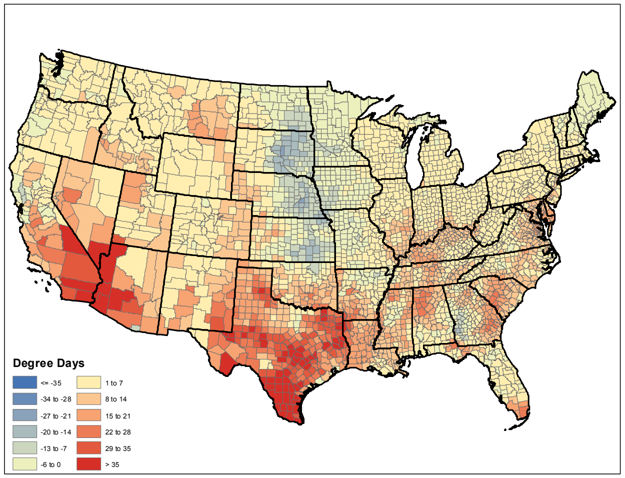
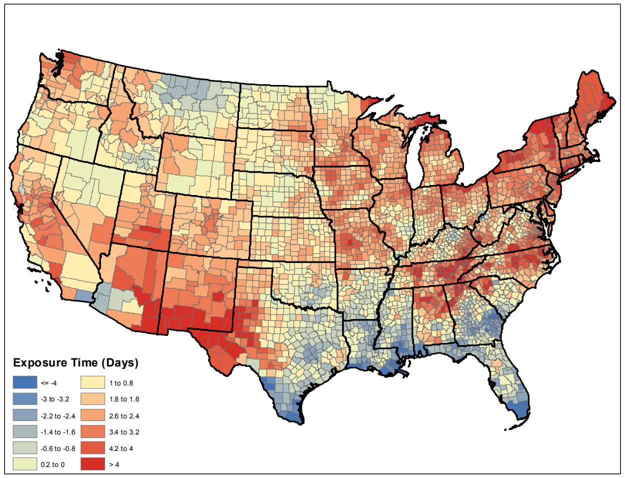
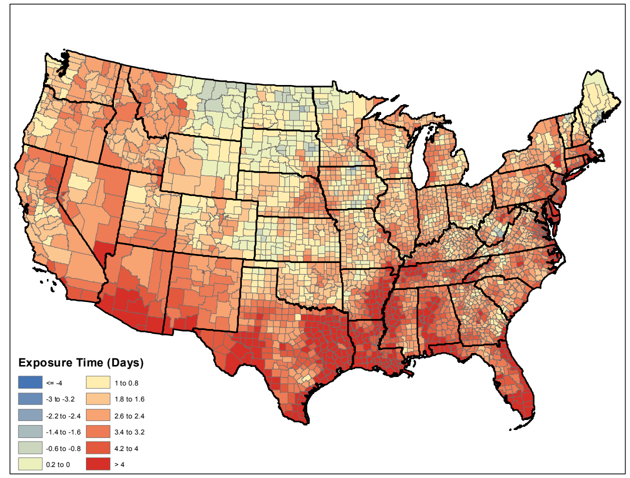


Figure 1.6: Maps of Changes in Temperature Exposure, 1982-2012 (All Months)

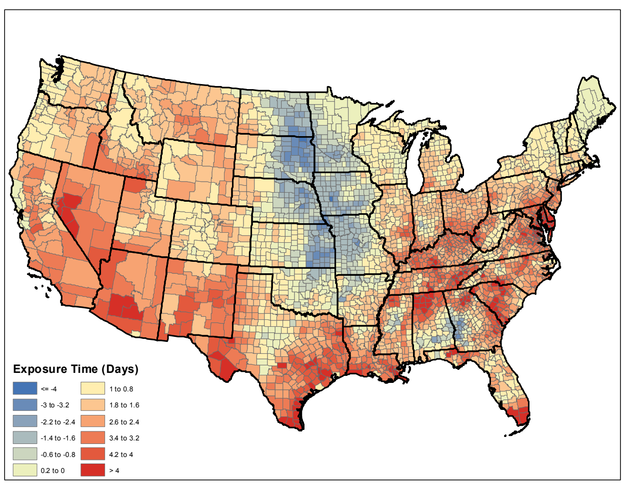
(a) Change in Avg Days Between 20°C and 25°C



(b) Change in Avg Days Between 25°C and 30°C



(c) Change in Avg Days Between 30°C and 35°C



(d) Change in Avg Days Above 35°C

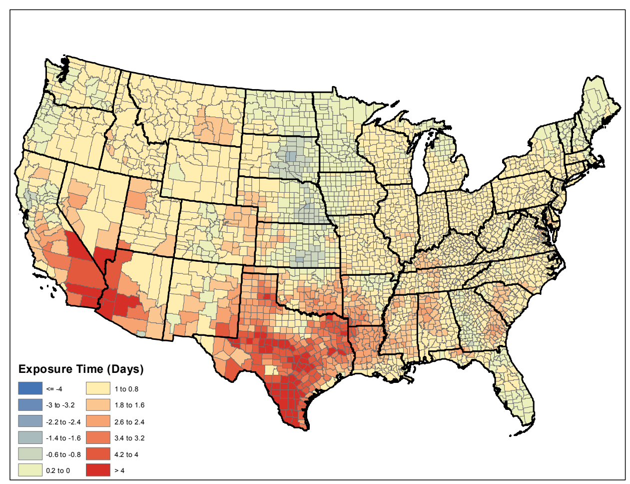


Table 1.1: Broad Land Use Transitions for all Non-Federal Land using the National Resources Inventory, 1982-2012, Thousands of Acres

	2012 Land Use									
	Cultivated Cropland	Noncultivated Cropland	Pasture	Range	Forest	Developed	CRP	Other	Total in 1982	Switched since 1982
1982 Land Use										
Cultivated Cropland	276,014	22,817	27,223	5,059	8,523	9,233	21,306	3,295	373,470	97,457
Noncultivated Cropland	11,735	17,607	7,685	1,096	1,642	2,453	780	893	43,892	26,285
Pasture	12,272	8,508	74,265	4,569	19,579	6,767	1,025	2,361	129,346	55,081
Range	6,358	1,804	3,818	387,106	3,405	5,746	902	2,716	411,854	24,748
Forest	1,657	756	5,739	2,502	372,393	17,612	116	2,676	403,450	31,057
Developed	273	59	183	183	477	70,246	2	43	71,465	1,220
Other	1,340	362	1,381	1,121	3,681	1,172	83	32,642	41,782	9,140
Total in 2012	309,649	51,914	120,295	401,636	409,699	113,227	24,213	44,625	1,475,259	
New since 1982	33,635	34,306	46,030	14,531	37,307	42,982	24,213	11,984		

This table excludes any land that was federally owned at any point between 1982 and 2012. The developed category represents the combination of the "Urban and built-up" and "Rural transportation" categories, as in U.S. Department of Agriculture (2015). The "Other" category includes rural land in farmsteads, barren land, marshland, other land in farms, and permanent snow-ice. "CRP" represents land in the Conservation Reserve Program, which was not yet in existence in 1982.

Table 1.2: Summary Statistics of Broad Land Use Change by County, 1982-2012

	N	Mean	Std. Dev.	Min	Max
Change in Total County Acres (1,000s)					
Cultivated Cropland	3072	-20.78	34.47	-501.90	109.10
Noncultivated Cropland	3072	2.61	14.97	-87.30	365.60
Pasture	3072	-2.95	20.68	-155.00	123.70
Range	3072	-3.33	17.53	-252.80	120.30
Forest	3072	2.03	18.75	-131.00	206.00
Developed	3072	13.59	21.81	-9.30	455.90
Change as a Fraction of Total County Acres					
Cultivated Cropland	3072	-0.05	0.06	-0.41	0.14
Noncultivated Cropland	3072	0.01	0.03	-0.18	0.16
Pasture	3072	-0.01	0.05	-0.25	0.22
Range	3072	0.00	0.02	-0.28	0.18
Forest	3072	0.00	0.05	-0.45	0.27
Developed	3072	0.04	0.05	-0.04	0.50

This table uses the National Resources Inventory to report summary statistics of broad land use change by county for all non-federal land in the continental United States. Land is defined as in Table 1.1.

Table 1.3: How Much Variation in the Climate Variables Remains after Controlling for Fixed Effects?

	Climate in 1982			Climate Change, 1982-2012		
	Constant Only	Constant + State Fixed Effects	% Absorbed	Constant Only	Constant + State Fixed Effects	% Absorbed
$\bar{D} \in [10, 15)$	4.41	2.46	44%	1.18	0.86	27%
$\bar{D} \in [15, 20)$	6.70	2.57	62%	2.05	1.00	51%
$\bar{D} \in [20, 25)$	17.58	5.80	67%	1.89	1.34	29%
$\bar{D} \in [25, 30)$	15.22	5.92	61%	1.58	1.13	28%
$\bar{D} \in [30, 35)$	12.16	4.28	65%	1.88	1.15	39%
$\bar{D} \in [35, \infty)$	2.83	1.35	52%	0.99	0.60	39%
$\bar{DD} \in (0, 30]$	776.21	245.77	68%	62.18	38.90	37%
$\bar{DD} \in (30, \infty]$	42.12	15.52	63%	10.12	6.03	40%
$\bar{P}$	28.63	11.60	59%	8.92	4.57	49%
$\Delta\bar{P} \geq 0$				4.92	2.82	43%
$\Delta\bar{P} < 0$				5.26	3.06	42%

This table reports the standard deviation of residuals from regressions that use the climate variables, given by the row, as dependent variables. There are two sets of regressions: the first set, columns (1)-(3), uses the level climate measures from 1982, while the second set, columns (4)-(6), uses the observed changes between 1982 and 2012. These measures are regressed either on a constant only, columns (1) & (4), or a constant with state fixed effects, columns (2) & (5). The standard deviation is a measure of the climate variation that remains after controlling for fixed effects, as in Fisher et al. (2012).

Table 1.4: Preliminary Analysis of Variation in Long Differences Estimates Between the East and the West: LPM for Cultivated Cropland

	All Counties All Points		All Counties Non-Irrigated		East of 100^{th} Non-Irrigated		West of 100^{th} Non-Irrigated	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\bar{D} \in [10, 15)$	-0.0108**		-0.0100**		-0.0083		-0.0039	
	(0.0044)		(0.0049)		(0.0058)		(0.0100)	
$\Delta\bar{D} \in [15, 20)$	-0.0121***		-0.0107**		-0.0147***		-0.0052	
	(0.0036)		(0.0042)		(0.0051)		(0.0075)	
$\Delta\bar{D} \in [20, 25)$	-0.0051		-0.0085**		-0.0133***		-0.0126	
	(0.0033)		(0.0036)		(0.0041)		(0.0105)	
$\Delta\bar{D} \in [25, 30)$	0.0090**		0.0200***		0.0264***		0.0001	
	(0.0044)		(0.0048)		(0.0054)		(0.0109)	
$\Delta\bar{D} \in [30, 35)$	-0.0069*		-0.0117***		-0.0084*		-0.0541***	
	(0.0042)		(0.0044)		(0.0047)		(0.0134)	
$\Delta\bar{D} \in [35, \infty)$	-0.0344***		-0.0289***		-0.0422***		0.0244*	
	(0.0073)		(0.0085)		(0.0099)		(0.0141)	
$\Delta\bar{D}D \in (0, 30]$		0.0002		0.0003**		0.0005***		-0.0010***
		(0.0001)		(0.0002)		(0.0002)		(0.0003)
$\Delta\bar{D}D \in (30, \infty]$		-0.0030***		-0.0037***		-0.0047***		0.0019
		(0.0008)		(0.0009)		(0.0011)		(0.0017)
$\Delta\bar{P} \geq 0$	0.0029**	0.0019	0.0030**	0.0022	0.0028*	0.0018	-0.0139***	-0.0112**
	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0054)	(0.0055)
$\Delta\bar{P} < 0$	0.0050***	0.0043**	0.0032	0.0019	0.0010	0.0002	0.0256***	0.0232***
	(0.0018)	(0.0018)	(0.0020)	(0.0021)	(0.0021)	(0.0022)	(0.0069)	(0.0065)
N	240,588	240,588	209,339	209,339	181,354	181,354	27,985	27,985
R^2	0.1233	0.1214	0.1290	0.1264	0.1385	0.1341	0.0958	0.0918

Regressions in this table use NRI points that are in cultivated cropland in 1982. The dependent variable equals 1 for points that continue to be used for cultivated cropland in 2012. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $^\circ$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{D}D$ are changes in degree days; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.5: Long-Difference Linear Probability Models for Cultivated Cropland as the Base Land Use in 1982 using Average Time in Temperature Intervals

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta\bar{D} \in [10, 15)$	-0.0083	0.0003	-0.0011	-0.0012**	-0.0004	0.0053
	(0.0058)	(0.0017)	(0.0017)	(0.0006)	(0.0011)	(0.0047)
$\Delta\bar{D} \in [15, 20)$	-0.0147***	0.0084***	0.0024	0.0010***	0.0032***	0.0008
	(0.0051)	(0.0015)	(0.0015)	(0.0003)	(0.0010)	(0.0041)
$\Delta\bar{D} \in [20, 25)$	-0.0133***	-0.0017	0.0040***	-0.0002	-0.0027***	0.0132***
	(0.0041)	(0.0011)	(0.0014)	(0.0004)	(0.0010)	(0.0035)
$\Delta\bar{D} \in [25, 30)$	0.0264***	-0.0084***	-0.0110***	0.0004	0.0006	-0.0045
	(0.0054)	(0.0014)	(0.0018)	(0.0007)	(0.0012)	(0.0036)
$\Delta\bar{D} \in [30, 35)$	-0.0084*	0.0017	-0.0015	-0.0005	-0.0047***	0.0134***
	(0.0047)	(0.0013)	(0.0016)	(0.0007)	(0.0013)	(0.0034)
$\Delta\bar{D} \in [35, \infty)$	-0.0422***	0.0020	0.0196***	0.0048*	0.0103***	0.0000
	(0.0099)	(0.0020)	(0.0047)	(0.0027)	(0.0017)	(0.0093)
$\Delta\bar{P} \geq 0$	0.0028*	-0.0015***	-0.0003	-0.0001*	-0.0009***	0.0005
	(0.0015)	(0.0005)	(0.0004)	(0.0001)	(0.0002)	(0.0012)
$\Delta\bar{P} < 0$	0.0010	-0.0011***	-0.0022***	0.0001	0.0018***	0.0001
	(0.0021)	(0.0004)	(0.0008)	(0.0002)	(0.0005)	(0.0016)
N	181,354	181,354	181,354	181,354	181,354	181,354
R^2	0.1385	0.0364	0.0397	0.0393	0.0894	0.0831

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in cultivated cropland in 1982 and are not irrigated. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $^\circ$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.6: Long-Difference Linear Probability Models for Noncultivated Cropland as the Base Land Use in 1982 using Average Time in Temperature Intervals

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta\bar{D} \in [10, 15)$	-0.0208***	0.0216***	0.0044	-0.0002	0.0042**	-0.0115
	(0.0061)	(0.0067)	(0.0049)	(0.0010)	(0.0021)	(0.0083)
$\Delta\bar{D} \in [15, 20)$	-0.0107**	0.0058	-0.0021	0.0003	0.0023	0.0068
	(0.0051)	(0.0053)	(0.0034)	(0.0008)	(0.0018)	(0.0064)
$\Delta\bar{D} \in [20, 25)$	0.0056	-0.0036	-0.0020	-0.0010	-0.0027	0.0058
	(0.0036)	(0.0048)	(0.0036)	(0.0006)	(0.0018)	(0.0065)
$\Delta\bar{D} \in [25, 30)$	-0.0033	-0.0059	-0.0046	-0.0013	0.0074***	0.0060
	(0.0054)	(0.0059)	(0.0049)	(0.0009)	(0.0023)	(0.0068)
$\Delta\bar{D} \in [30, 35)$	-0.0089	0.0053	-0.0088*	0.0005	-0.0023	0.0138**
	(0.0057)	(0.0057)	(0.0046)	(0.0016)	(0.0022)	(0.0068)
$\Delta\bar{D} \in [35, \infty)$	-0.0212	-0.0136	0.0286**	0.0015	0.0066	0.0062
	(0.0138)	(0.0127)	(0.0140)	(0.0069)	(0.0045)	(0.0197)
$\Delta\bar{P} \geq 0$	0.0027*	-0.0059***	0.0012	-0.0003	-0.0010*	0.0028
	(0.0014)	(0.0016)	(0.0012)	(0.0003)	(0.0005)	(0.0018)
$\Delta\bar{P} < 0$	0.0016	-0.0018	-0.0047***	0.0006	0.0002	0.0051*
	(0.0017)	(0.0020)	(0.0016)	(0.0004)	(0.0008)	(0.0029)
N	22,119	22,119	22,119	22,119	22,119	22,119
R^2	0.1534	0.0320	0.0381	0.0441	0.0241	0.0867

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in noncultivated cropland in 1982 and are not irrigated. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $^\circ$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in $5^\circ\mathrm{C}$ bins; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.7: Long-Difference Linear Probability Models for Pasture as the Base Land Use in 1982 using Average Time in Temperature Intervals

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta\bar{D} \in [10, 15)$	-0.0019	0.0011	0.0035	-0.0060***	0.0156***	-0.0157**
	(0.0021)	(0.0013)	(0.0053)	(0.0012)	(0.0023)	(0.0062)
$\Delta\bar{D} \in [15, 20)$	-0.0084***	0.0011	0.0047	0.0005	0.0050**	-0.0036
	(0.0017)	(0.0011)	(0.0038)	(0.0007)	(0.0022)	(0.0047)
$\Delta\bar{D} \in [20, 25)$	-0.0054***	-0.0006	0.0058*	-0.0012**	-0.0027	0.0041
	(0.0012)	(0.0008)	(0.0034)	(0.0006)	(0.0016)	(0.0039)
$\Delta\bar{D} \in [25, 30)$	0.0074***	-0.0009	-0.0297***	-0.0041***	0.0157***	0.0115***
	(0.0019)	(0.0009)	(0.0035)	(0.0012)	(0.0022)	(0.0042)
$\Delta\bar{D} \in [30, 35)$	-0.0090***	-0.0013	-0.0087**	-0.0003	-0.0119***	0.0333***
	(0.0017)	(0.0010)	(0.0041)	(0.0011)	(0.0022)	(0.0044)
$\Delta\bar{D} \in [35, \infty)$	0.0008	-0.0011	-0.0017	0.0000	0.0152***	-0.0208**
	(0.0027)	(0.0012)	(0.0078)	(0.0043)	(0.0039)	(0.0086)
$\Delta\bar{P} \geq 0$	0.0000	-0.0012***	-0.0005	-0.0004*	-0.0009	0.0030*
	(0.0007)	(0.0004)	(0.0014)	(0.0003)	(0.0007)	(0.0016)
$\Delta\bar{P} < 0$	0.0004	-0.0003	-0.0059***	0.0005	-0.0018**	0.0068***
	(0.0005)	(0.0003)	(0.0014)	(0.0004)	(0.0008)	(0.0015)
N	87,730	87,730	87,730	87,730	87,730	87,730
R^2	0.0612	0.0165	0.0430	0.0541	0.0385	0.0597

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in pasture in 1982 and are not irrigated. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $^\circ$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.8: Long-Difference Linear Probability Models for Range as the Base Land Use in 1982 using Average Time in Temperature Intervals

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta\bar{D} \in [10, 15)$	-0.0062***	0.0008*	0.0134***	-0.0733***	0.0094***	0.0451***
	(0.0015)	(0.0005)	(0.0029)	(0.0133)	(0.0022)	(0.0121)
$\Delta\bar{D} \in [15, 20)$	0.0032*	-0.0009	-0.0013	-0.0358***	-0.0006	0.0315***
	(0.0019)	(0.0006)	(0.0021)	(0.0087)	(0.0016)	(0.0082)
$\Delta\bar{D} \in [20, 25)$	0.0029**	-0.0007	-0.0032**	0.0096	-0.0022**	-0.0081
	(0.0013)	(0.0004)	(0.0015)	(0.0063)	(0.0010)	(0.0058)
$\Delta\bar{D} \in [25, 30)$	0.0002	0.0003	-0.0010	-0.0327***	0.0017**	0.0282***
	(0.0009)	(0.0004)	(0.0014)	(0.0080)	(0.0007)	(0.0075)
$\Delta\bar{D} \in [30, 35)$	0.0034**	-0.0007	0.0001	-0.0401***	-0.0017	0.0348***
	(0.0014)	(0.0005)	(0.0019)	(0.0088)	(0.0013)	(0.0084)
$\Delta\bar{D} \in [35, \infty)$	-0.0023***	0.0001	0.0002	-0.0041	0.0027***	0.0027
	(0.0008)	(0.0002)	(0.0014)	(0.0072)	(0.0008)	(0.0065)
$\Delta\bar{P} \geq 0$	0.0012	0.0002	0.0014*	-0.0052*	-0.0002	0.0021
	(0.0008)	(0.0002)	(0.0007)	(0.0027)	(0.0005)	(0.0026)
$\Delta\bar{P} < 0$	0.0002	-0.0002	-0.0031***	0.0018	-0.0001	0.0022
	(0.0003)	(0.0001)	(0.0007)	(0.0031)	(0.0004)	(0.0029)
N	46,989	46,989	46,989	46,989	46,989	46,989
R^2	0.0232	0.0055	0.0220	0.1128	0.0304	0.1100

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in range in 1982. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in °C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in $5°$C bins; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.9: Long-Difference Linear Probability Models for Forest as the Base Land Use in 1982 using Average Time in Temperature Intervals

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta\bar{D} \in [10, 15)$	0.0008***	-0.0000	0.0010***	-0.0004***	0.0193***	-0.0217***
	(0.0002)	(0.0001)	(0.0004)	(0.0001)	(0.0048)	(0.0049)
$\Delta\bar{D} \in [15, 20)$	-0.0009***	-0.0000	0.0001	0.0001*	0.0025	-0.0021
	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0038)	(0.0038)
$\Delta\bar{D} \in [20, 25)$	-0.0007***	-0.0001	0.0009***	0.0000	0.0004	-0.0009
	(0.0001)	(0.0001)	(0.0003)	(0.0000)	(0.0033)	(0.0033)
$\Delta\bar{D} \in [25, 30)$	0.0012***	-0.0001	-0.0015***	-0.0001*	-0.0070	0.0080*
	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0045)	(0.0046)
$\Delta\bar{D} \in [30, 35)$	-0.0004*	0.0001	0.0007**	0.0001	-0.0317***	0.0316***
	(0.0002)	(0.0001)	(0.0004)	(0.0001)	(0.0046)	(0.0046)
$\Delta\bar{D} \in [35, \infty)$	0.0002	-0.0001	-0.0013	-0.0006*	0.0479***	-0.0494***
	(0.0005)	(0.0002)	(0.0010)	(0.0003)	(0.0102)	(0.0103)
$\Delta\bar{P} \geq 0$	0.0001	-0.0000	-0.0002	0.0000	-0.0074***	0.0077***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0014)	(0.0014)
$\Delta\bar{P} < 0$	0.0000	0.0000	-0.0000	0.0001***	-0.0007	0.0004
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0012)	(0.0012)
N	258,158	258,158	258,158	258,158	258,158	258,158
R^2	0.0040	0.0007	0.0058	0.0087	0.0421	0.0494

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in forest in 1982. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $^\circ$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.10: Long-Difference Linear Probability Models for Cultivated Cropland as the Base Land Use in 1982 using Piecewise Linear Degree Days with Threshold at $30°\text{C}$

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta\bar{DD} \in (0, 30]$	0.0005***	-0.0002***	-0.0003***	-0.0000	-0.0001***	0.0003**
	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
$\Delta\bar{DD} \in (30, \infty]$	-0.0047***	0.0009***	0.0021***	0.0003	0.0008***	-0.0003
	(0.0011)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0009)
$\Delta\bar{P} \geq 0$	0.0018	-0.0013***	0.0001	-0.0001	-0.0006***	0.0005
	(0.0015)	(0.0005)	(0.0004)	(0.0001)	(0.0002)	(0.0012)
$\Delta\bar{P} < 0$	0.0002	-0.0008*	-0.0021**	-0.0000	0.0017***	0.0006
	(0.0022)	(0.0005)	(0.0008)	(0.0002)	(0.0005)	(0.0016)
N	181,354	181,354	181,354	181,354	181,354	181,354
R^2	0.1341	0.0341	0.0376	0.0386	0.0882	0.0819

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in cultivated cropland in 1982 and are not irrigated. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $°\text{C}$; precipitation is in cm. $\Delta\bar{DD}$ are changes in degree days; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.11: Long-Difference Linear Probability Models for Noncultivated Cropland as the Base Land Use in 1982 using Piecewise Linear Degree Days with Threshold at $30°\text{C}$

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta \bar{DD} \in (0, 30]$	0.0001	-0.0003	-0.0004**	-0.0001	0.0001	0.0006***
	(0.0002)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
$\Delta \bar{DD} \in (30, \infty]$	-0.0022*	-0.0003	0.0022*	0.0005	-0.0001	-0.0001
	(0.0013)	(0.0014)	(0.0012)	(0.0005)	(0.0005)	(0.0019)
$\Delta \bar{P} \geq 0$	0.0028*	-0.0061***	0.0013	-0.0003	-0.0009	0.0029*
	(0.0015)	(0.0016)	(0.0011)	(0.0003)	(0.0005)	(0.0017)
$\Delta \bar{P} < 0$	0.0006	-0.0007	-0.0050***	0.0006	0.0003	0.0049*
	(0.0016)	(0.0020)	(0.0016)	(0.0004)	(0.0009)	(0.0029)
N	22,119	22,119	22,119	22,119	22,119	22,119
R^2	0.1505	0.0298	0.0375	0.0441	0.0230	0.0860

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in noncultivated cropland in 1982 and are not irrigated. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $°\text{C}$; precipitation is in cm. $\Delta \bar{DD}$ are changes in degree days; $\Delta \bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.12: Long-Difference Linear Probability Models for Pasture as the Base Land Use in 1982 using Piecewise Linear Degree Days with Threshold at $30°\text{C}$

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta \bar{DD} \in (0, 30]$	-0.0000	-0.0001**	-0.0008***	-0.0001***	0.0001	0.0010***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
$\Delta \bar{DD} \in (30, \infty]$	-0.0004	-0.0000	0.0015	0.0004	-0.0006	-0.0014
	(0.0003)	(0.0001)	(0.0010)	(0.0004)	(0.0005)	(0.0010)
$\Delta \bar{P} \geq 0$	-0.0002	-0.0011***	-0.0001	-0.0004*	-0.0008	0.0026
	(0.0007)	(0.0004)	(0.0014)	(0.0003)	(0.0007)	(0.0016)
$\Delta \bar{P} < 0$	-0.0000	-0.0002	-0.0050***	0.0004	-0.0016**	0.0063***
	(0.0004)	(0.0003)	(0.0014)	(0.0004)	(0.0008)	(0.0015)
N	87,730	87,730	87,730	87,730	87,730	87,730
R^2	0.0587	0.0165	0.0404	0.0519	0.0341	0.0548

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in pasture in 1982 and are not irrigated. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $°\text{C}$; precipitation is in cm. $\Delta \bar{DD}$ are changes in degree days; $\Delta \bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.13: Long-Difference Linear Probability Models for Range as the Base Land Use in 1982 using Piecewise Linear Degree Days with Threshold at $30°\mathrm{C}$

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta \bar{DD} \in (0, 30]$	0.0001***	-0.0000	-0.0001**	-0.0014***	-0.0000	0.0012***
	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0003)
$\Delta \bar{DD} \in (30, \infty]$	-0.0004***	0.0000	-0.0001	0.0041***	0.0001	-0.0031***
	(0.0001)	(0.0000)	(0.0002)	(0.0011)	(0.0001)	(0.0010)
$\Delta \bar{P} \geq 0$	0.0011	0.0002	0.0012*	-0.0057**	-0.0000	0.0026
	(0.0008)	(0.0002)	(0.0007)	(0.0025)	(0.0005)	(0.0025)
$\Delta \bar{P} < 0$	0.0002	-0.0002	-0.0030***	0.0020	0.0000	0.0016
	(0.0003)	(0.0001)	(0.0007)	(0.0032)	(0.0003)	(0.0029)
N	46,989	46,989	46,989	46,989	46,989	46,989
R^2	0.0217	0.0052	0.0182	0.0925	0.0265	0.0891

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in range in 1982. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $°\mathrm{C}$; precipitation is in cm. $\Delta \bar{DD}$ are changes in degree days; $\Delta \bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.14: Long-Difference Linear Probability Models for Forest as the Base Land Use in 1982 using Piecewise Linear Degree Days with Threshold at $30°\mathrm{C}$

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta \bar{DD} \in (0, 30]$	0.0000	-0.0000	-0.0000	0.0000	-0.0007***	0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
$\Delta \bar{DD} \in (30, \infty]$	0.0000	0.0000**	0.0000	-0.0000	0.0010	-0.0012
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0010)	(0.0010)
$\Delta \bar{P} \geq 0$	0.0001*	-0.0000	-0.0002*	0.0000	-0.0079***	0.0081***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0014)	(0.0014)
$\Delta \bar{P} < 0$	0.0001	0.0000	-0.0000	0.0001***	-0.0002	-0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0012)	(0.0012)
N	258,158	258,158	258,158	258,158	258,158	258,158
R^2	0.0032	0.0007	0.0055	0.0084	0.0366	0.0430

Regressions in these tables use NRI points in counties east of the 100^{th} meridian that are in forest in 1982. The dependent variable equals 1 for points that in 2012 are associated with the land use given by the column. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $°\mathrm{C}$; precipitation is in cm. $\Delta \bar{DD}$ are changes in degree days; $\Delta \bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.15: Long-Difference Linear Probability Models for Switching to New Land Uses (columns) From All Other Land Uses Combined using Average Time in Temperature Intervals

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta\bar{D} \in [10, 15)$	-0.0021***	-0.0009**	0.0001	-0.0011***	0.0051***	-0.0083**
	(0.0006)	(0.0004)	(0.0006)	(0.0002)	(0.0008)	(0.0038)
$\Delta\bar{D} \in [15, 20)$	-0.0032***	0.0002	-0.0005	0.0003**	0.0033***	0.0007
	(0.0006)	(0.0003)	(0.0004)	(0.0001)	(0.0007)	(0.0030)
$\Delta\bar{D} \in [20, 25)$	-0.0020***	-0.0013***	-0.0009**	-0.0002**	-0.0005	0.0046*
	(0.0003)	(0.0002)	(0.0004)	(0.0001)	(0.0006)	(0.0026)
$\Delta\bar{D} \in [25, 30)$	0.0014***	-0.0019***	-0.0031***	-0.0009***	0.0015*	0.0051
	(0.0005)	(0.0003)	(0.0005)	(0.0003)	(0.0008)	(0.0033)
$\Delta\bar{D} \in [30, 35)$	-0.0028***	-0.0002	-0.0006	-0.0003	-0.0029***	0.0221***
	(0.0005)	(0.0003)	(0.0005)	(0.0002)	(0.0008)	(0.0030)
$\Delta\bar{D} \in [35, \infty)$	-0.0019***	-0.0007**	0.0006	0.0010	0.0055***	-0.0149***
	(0.0006)	(0.0004)	(0.0011)	(0.0012)	(0.0011)	(0.0057)
$\Delta\bar{P} \geq 0$	0.0004*	-0.0003**	-0.0001	-0.0001	-0.0008***	0.0040***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0009)
$\Delta\bar{P} < 0$	0.0001	-0.0001	-0.0006***	0.0002**	-0.0003	0.0010
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.0011)
N	653469	812704	747093	787834	576665	666348
R^2	0.0303	0.0065	0.0073	0.0226	0.0279	0.0627

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are not irrigated in 1982. Each column further restricts the sample to points that were not associated with the land use given by the column in 1982. The dependent variable equals 1 for points that have transitioned by 2012 to the column land use. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $^\circ$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.16: Long-Difference Linear Probability Models for Switching to New Land Uses (columns) From All Other Land Uses Combined using Piecewise Linear Degree Days with Threshold at $30°\text{C}$

	2012 Land Use					
	Cultivated Cropland (1)	Noncultivated Cropland (2)	Pasture (3)	Range (4)	Forest (5)	Developed (6)
$\Delta\bar{DD} \in (0, 30]$	-0.0000**	-0.0001***	-0.0001***	-0.0000***	-0.0001***	0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
$\Delta\bar{DD} \in (30, \infty]$	-0.0001	0.0002***	0.0004***	0.0001	0.0002	-0.0012*
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0007)
$\Delta\bar{P} \geq 0$	0.0004*	-0.0003**	-0.0001	-0.0000	-0.0007***	0.0037***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0009)
$\Delta\bar{P} < 0$	-0.0000	-0.0001	-0.0006***	0.0001*	-0.0001	0.0007
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.0011)
N	653469	812704	747093	787834	576665	666348
R^2	0.0296	0.0064	0.0073	0.0222	0.0267	0.0604

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are not irrigated in 1982. Each column further restricts the sample to points that were not associated with the land use given by the column in 1982. The dependent variable equals 1 for points that have transitioned by 2012 to the column land use. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. Temperature variable names are expressed in $°\text{C}$; precipitation is in cm. $\Delta\bar{DD}$ are changes in degree days; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.17: Robustness: End Year for Long Differences: LPM for Cultivated Cropland

	2002		2007		2012	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\bar{D} \in [10, 15)$	0.0192***		0.0027		-0.0083	
	(0.0054)		(0.0062)		(0.0058)	
$\Delta\bar{D} \in [15, 20)$	-0.0058		-0.0156***		-0.0147***	
	(0.0043)		(0.0050)		(0.0051)	
$\Delta\bar{D} \in [20, 25)$	-0.0138***		-0.0187***		-0.0133***	
	(0.0043)		(0.0042)		(0.0041)	
$\Delta\bar{D} \in [25, 30)$	0.0228***		0.0316***		0.0264***	
	(0.0057)		(0.0050)		(0.0054)	
$\Delta\bar{D} \in [30, 35)$	-0.0030		-0.0061		-0.0084*	
	(0.0047)		(0.0048)		(0.0047)	
$\Delta\bar{D} \in [35, \infty)$	-0.0091		-0.0330***		-0.0422***	
	(0.0073)		(0.0097)		(0.0099)	
$\Delta\bar{DD} \in (0, 30]$		0.0001		0.0004***		0.0005***
		(0.0002)		(0.0002)		(0.0002)
$\Delta\bar{DD} \in (30, \infty]$		-0.0017*		-0.0036***		-0.0047***
		(0.0009)		(0.0011)		(0.0011)
$\Delta\bar{P} \geq 0$	-0.0023	-0.0034**	0.0076***	0.0070***	0.0028*	0.0018
	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0015)
$\Delta\bar{P} < 0$	0.0104***	0.0112***	0.0048***	0.0055***	0.0010	0.0002
	(0.0020)	(0.0021)	(0.0016)	(0.0018)	(0.0021)	(0.0022)
N	181,354	181,354	181,354	181,354	181,354	181,354
R^2	0.1172	0.1128	0.1331	0.1268	0.1385	0.1341

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in cultivated cropland in 1982 and are not irrigated. The dependent variable equals 1 for points that continue to be used for cultivated cropland in the end year. All temperature and precipitation variables represent changes in 10-year averages between 1982 and the specified end year. Temperature variable names are expressed in $^\circ$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{DD}$ are changes in degree days; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.18: Robustness: Length of Average Weather Series in Long Differences – LPM for Cultivated Cropland

	5-Years		10-Years		15-Years		20-Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\bar{D} \in [10, 15)$	-0.0101***		-0.0083		0.0095		0.0043	
	(0.0038)		(0.0058)		(0.0072)		(0.0073)	
$\Delta\bar{D} \in [15, 20)$	-0.0163***		-0.0147***		-0.0208***		-0.0181***	
	(0.0039)		(0.0051)		(0.0060)		(0.0059)	
$\Delta\bar{D} \in [20, 25)$	0.0151***		-0.0133***		-0.0146***		-0.0214***	
	(0.0036)		(0.0041)		(0.0045)		(0.0052)	
$\Delta\bar{D} \in [25, 30)$	-0.0028		0.0264***		0.0306***		0.0393***	
	(0.0043)		(0.0054)		(0.0057)		(0.0063)	
$\Delta\bar{D} \in [30, 35)$	0.0025		-0.0084*		-0.0111**		-0.0191***	
	(0.0041)		(0.0047)		(0.0052)		(0.0058)	
$\Delta\bar{D} \in [35, \infty)$	-0.0140*		-0.0422***		-0.0206**		-0.0271**	
	(0.0084)		(0.0099)		(0.0095)		(0.0109)	
$\Delta\bar{D}D \in (0, 30]$		0.0003**		0.0005***		0.0003**		0.0003*
		(0.0001)		(0.0002)		(0.0002)		(0.0002)
$\Delta\bar{D}D \in (30, \infty]$		-0.0008		-0.0047***		-0.0025**		-0.0035***
		(0.0009)		(0.0011)		(0.0011)		(0.0013)
$\Delta\bar{P} \geq 0$	-0.0024**	-0.0030***	0.0028*	0.0018	0.0017	0.0013	-0.0013	-0.0019
	(0.0010)	(0.0009)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0015)	(0.0015)
$\Delta\bar{P} < 0$	-0.0036**	-0.0037**	0.0010	0.0002	0.0015	0.0018	0.0044	0.0045
	(0.0017)	(0.0017)	(0.0021)	(0.0022)	(0.0027)	(0.0031)	(0.0039)	(0.0045)
N	181,354	181,354	181,354	181,354	181,354	181,354	181,354	181,354
R^2	0.1381	0.1344	0.1385	0.1341	0.1382	0.1329	0.1393	0.1331

Regressions in this table use NRI points in counties east of the 100^{th} meridian that are in cultivated cropland in 1982 and are not irrigated. The dependent variable equals 1 for points that continue to be used for cultivated cropland in 2012. All temperature and precipitation variables represent changes in n-year averages, as specified by the column, between 1982 and 2012. Temperature variable names are expressed in $^{\circ}$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{D}D$ are changes in degree days; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.19: The Effect of Observed Climate Change (1982-2012) on New Ethanol Production (2002-2012) at the County Level

	Change in Ethanol Production (mgy)			Probability of a New Plant	
	East 100 (1)	East 100, Upper Midwest (2)	East 100, Upper Midwest, $\text{Production}_{2002} > 0$ (3)	East 100 (4)	East 100, Upper Midwest (5)
$\Delta\bar{D} \in [10, 15)$	-0.4232	-0.8798	4.1987	-0.0062	-0.0200
	(0.4481)	(1.4528)	(27.6381)	(0.0046)	(0.0147)
$\Delta\bar{D} \in [15, 20)$	0.1435	0.2738	4.6509	0.0023	0.0074
	(0.2989)	(1.0245)	(14.5133)	(0.0034)	(0.0113)
$\Delta\bar{D} \in [20, 25)$	0.5401***	2.7996**	-11.7322	0.0029	0.0140
	(0.2056)	(1.1122)	(21.5105)	(0.0021)	(0.0119)
$\Delta\bar{D} \in [25, 30)$	0.2730	-0.1532	15.3944	0.0009	-0.0077
	(0.3050)	(1.4440)	(21.6068)	(0.0028)	(0.0144)
$\Delta\bar{D} \in [30, 35)$	-0.3818	-0.1720	-21.5017	-0.0030	0.0046
	(0.2782)	(1.0293)	(18.9928)	(0.0032)	(0.0125)
$\Delta\bar{D} \in [35, \infty)$	0.1486	-1.4894	39.5137	-0.0010	-0.0376
	(0.3362)	(2.8851)	(52.2150)	(0.0033)	(0.0287)
$\Delta\bar{P} \geq 0$	0.2584	0.4813	4.4633	0.0037**	0.0083**
	(0.1616)	(0.3096)	(5.8753)	(0.0017)	(0.0033)
$\Delta\bar{P} < 0$	0.0323	0.3297	6.0162	-0.0004	-0.0015
	(0.0621)	(0.5058)	(8.1079)	(0.0007)	(0.0072)
N	2,506	956	42	2,506	956
R^2	0.1286	0.0930	0.2521	0.1254	0.0779

Regressions in this table use Ethanol production data between 2002 and 2012 from McWilliams and Moore (2016a). The dependent variable in columns (1)-(3) is the total change in operating capacity for all refineries in a county between 2002 and 2012. The dependent variable in columns (4)-(5) is a dummy variable equal to 1 if a new ethanol refinery was constructed in the county. Columns (1) and (4) restrict the sample to counties east of the 100^{th} meridian. Columns (2) and (5) further restrict to the following Upper Midwest states: IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, and WI. Column (3) further restricts to counties with positive ethanol production in 2002. All temperature and precipitation variables represent changes in 10-year averages between 1982 and 2012. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{P}$ are changes in precipitation (cm). All regressions include state fixed effects and a constant. Eicker-Huber-White standard errors are reported in parentheses. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.20: The Effects of Observed Climate Change on the Probability of Irrigation Adoption, 1982-2012

	All NRI Points in Lower-48		NRI Points East of 100^{th} Meridian		NRI Poinst West of 100^{th} Meridian	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \bar{D} \in [10, 15)$	0.0071***		0.0061***		0.0122***	
	(0.0014)		(0.0015)		(0.0037)	
$\Delta \bar{D} \in [15, 20)$	-0.0036***		-0.0014		-0.0092***	
	(0.0011)		(0.0011)		(0.0031)	
$\Delta \bar{D} \in [20, 25)$	-0.0015		-0.0064***		0.0084**	
	(0.0011)		(0.0011)		(0.0035)	
$\Delta \bar{D} \in [25, 30)$	0.0109***		0.0153***		0.0014	
	(0.0021)		(0.0024)		(0.0055)	
$\Delta \bar{D} \in [30, 35)$	0.0031**		0.0021		0.0104**	
	(0.0014)		(0.0015)		(0.0047)	
$\Delta \bar{D} \in [35, \infty)$	-0.0154***		-0.0126***		-0.0365***	
	(0.0030)		(0.0033)		(0.0070)	
$\Delta \bar{D}D \in (0, 30]$		0.0003***		0.0003***		0.0005***
		(0.0001)		(0.0001)		(0.0001)
$\Delta \bar{D}D \in (30, \infty]$		-0.0023***		-0.0018***		-0.0054***
		(0.0003)		(0.0004)		(0.0008)
$\Delta \bar{P} \geq 0$	-0.0012***	-0.0015***	-0.0011***	-0.0014***	-0.0006	-0.0010
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0021)	(0.0018)
$\Delta \bar{P} < 0$	-0.0006	-0.0008	-0.0016*	-0.0017*	-0.0022	-0.0045
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0035)	(0.0033)
N	326,929	326,929	291,203	291,203	35,726	35,726
R^2	0.0642	0.0585	0.0735	0.0616	0.0524	0.0483

Regressions in this table use NRI points in the lower-48, continental U.S. that are in agricultural land uses (cultivated cropland, noncultivated cropland, or pasture) and are not irrigated in 1982. The dependent variable equals 1 for points that are irrigated in 2012. All temperature and precipitation variables represent changes in 10-year averages between 1982 and the specified end year. Temperature variable names are expressed in $^{\circ}$C; precipitation is in cm. $\Delta \bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta \bar{D}D$ are changes in degree days; $\Delta \bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 1.21: The Effects of Observed Climate Change on Irrigation Abandonment, 1982-2012

	All NRI Points in Lower-48		NRI Points East of 100^{th} Meridian		NRI Poinst West of 100^{th} Meridian	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\bar{D} \in [10, 15)$	-0.0119*		0.0032		-0.0171**	
	(0.0069)		(0.0147)		(0.0077)	
$\Delta\bar{D} \in [15, 20)$	0.0099*		0.0451***		0.0085	
	(0.0056)		(0.0141)		(0.0065)	
$\Delta\bar{D} \in [20, 25)$	0.0088*		0.0255**		0.0138*	
	(0.0051)		(0.0100)		(0.0082)	
$\Delta\bar{D} \in [25, 30)$	0.0163***		0.0056		0.0147	
	(0.0062)		(0.0079)		(0.0113)	
$\Delta\bar{D} \in [30, 35)$	-0.0115		0.0174*		-0.0236*	
	(0.0077)		(0.0100)		(0.0131)	
$\Delta\bar{D} \in [35, \infty)$	0.0220**		0.0121		0.0275*	
	(0.0107)		(0.0120)		(0.0150)	
$\Delta\bar{DD} \in (0, 30]$		0.0004*		0.0003		0.0004
		(0.0002)		(0.0003)		(0.0003)
$\Delta\bar{DD} \in (30, \infty]$		0.0004		-0.0014		0.0010
		(0.0011)		(0.0012)		(0.0014)
$\Delta\bar{P} \geq 0$	0.0120***	0.0122***	0.0008	0.0014	0.0350***	0.0366***
	(0.0042)	(0.0042)	(0.0044)	(0.0047)	(0.0070)	(0.0072)
$\Delta\bar{P} < 0$	-0.0116***	-0.0121***	-0.0037	-0.0035	-0.0258***	-0.0267***
	(0.0031)	(0.0027)	(0.0026)	(0.0024)	(0.0058)	(0.0057)
N	46,166	46,166	15,028	15,028	31,138	31,138
R^2	0.1006	0.0987	0.2299	0.2248	0.0457	0.0426

Regressions in this table use NRI points in the lower-48, continental U.S. that are in agricultural land uses (cultivated cropland, noncultivated cropland, or pasture) and are irrigated in 1982. The dependent variable equals 1 for points that are no longer irrigated in 2012. All temperature and precipitation variables represent changes in 10-year averages between 1982 and the specified end year. Temperature variable names are expressed in $^\circ$C; precipitation is in cm. $\Delta\bar{D}$ variables are changes in the number of days spent in 5°C bins; $\Delta\bar{DD}$ are changes in degree days; $\Delta\bar{P}$ are changes in precipitation. All regressions include state fixed effects and a constant. Standard errors are clustered at the county level. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

CHAPTER 2

Agglomeration in Agriculture: The Biofuel Quasi-Experiment in the Corn Belt

2.1 Introduction

The spatial concentration of economic activity (agglomeration) is most evident in urban areas, such that agglomeration economies are now used to explain the existence and composition of cities (Glaeser and Gottlieb, 2009). Is agglomeration also important in an agricultural context? In Krugman's seminal research on new economic geography, the "agricultural periphery" is featureless and thus uninteresting: immobile land worked by immobile peasants with costless transportation of agricultural products (Krugman, 1991). Yet this simply reflects the workings of an elegant model designed to elucidate agglomeration in the urban core. In fact, we observe substantial spatial concentration of agricultural activity in the United States. The Midwest, for example, houses seven of the top ten agricultural states, including a "Corn Belt" and a "Wheat Belt."[1] In addition, we observe agricultural-urban connections, rather than Krugman's bifurcation, in the major Midwestern cities of Chicago, Kansas City, Indianapolis, Minneapolis, and St. Louis, where backward linkages to agriculture seeded urban development and growth. Agriculture, undoubtedly, *is* the classic case for the importance of natural features — climate, soil, rainfall, and irrigation water

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[1] Illinois (#2), Iowa (#3), Nebraska (#4), Minnesota (#5), Indiana (#6), North Dakota (#8), and South Dakota (#10) are contiguous states in the American Midwest. The ranking is in terms of cash receipts for sales of agricultural crops.

— in explaining the location of economic activity (Holmes and Lee, 2012).[2] Nonetheless, the other agglomeration economies — knowledge spillovers, labor market pooling, and input-output linkages — are considered important to the spatial concentration of different crops and their related forward linkages to the agricultural processing sector (Holmes and Stevens, 2004). Agriculture and the rural sector, however, are understudied through the lens of agglomeration.

Our research illuminates the spatial economy of input-output linkages in the agricultural sector. We study, in particular, how the location of downstream industry explains spatial cropland use. Fujita et al. (1999) caution that relying on linkages as the basis for agglomeration often reduces to circular causation. An agricultural example is the co-location of growing and processing of sugar beets (Holmes and Stevens, 2004). The analyst observes the co-location but cannot identify which came first: field production of beets or the beet processing plant. Greenstone et al. (2010) solve the causation problem by using 47 distinct "million dollar plant" openings to study agglomeration externalities. We develop a similar quasi-experimental approach by using 130 recent openings of corn ethanol refineries in the Midwest to study spatial cropland use. Does the new demand for corn by refineries (of varying capacity at different locations in different years) affect spatial land allocations to corn, soybeans, wheat, and grassland?

A second topic of the paper concerns the role of refinery openings in generating spatial concentration in rural development. Widespread concern exists about the depopulation of rural counties throughout the United States, and particularly in parts of the Midwest (Hansen, 2003). Between 1980 and 2010, population decreased in rural counties in large portions of five states within the study area, including Iowa, Kansas, Nebraska, North Dakota, and South Dakota (Federal Deposit Insurance Corporation, 2014). Thome and Lin Lawell (2015) hypothesize that an intra-industry agglomeration effect might exist within the corn ethanol refinery sector, i.e., if several refineries have located in the same region, then a new plant might experience positive spillovers in the form of an educated workforce or an established marketing infrastructure. Yet they find that the agglomeration effect does not have a net strategic effect on the payoff from investing in an ethanol plant. Nevertheless, whether new ethanol plants spawn rural development is an open question. We address this by assessing land-use change with our quasi-experimental approach: does the opening of an ethanol plant result in an increase in developed land in the vicinity of the plant?

To answer the first question, we utilize the refinery opening quasi-experiment to identify

[2] Holmes and Lee (2012) find that approximately two-thirds of observed field-level crop concentrations in North Dakota can be explained by natural advantages, with the remaining one-third due to field-level density economies.

the effect of downstream industry on cropland use (crop choice). We first develop a model in which farmers choose crops based in part on the net price they receive, i.e., price minus transportation cost, leading crop choice to be correlated with proximity to downstream buyers. According to the model, a refinery opening induces a transportation cost shock that improves corn's profitability relative to alternative crops. The corn transportation cost reduction decreases as the road-distance from the refinery increases, and we generate a prediction of a positive distance-decay effect in corn land use and a negative distance decay-effect for soybeans and other substitute crops.

To test these predictions, we apply a 2002-2012 panel data set on land use relative to refinery location for the 130 refineries that opened in the Midwest during this period. Fourteen states are included in the study area: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Tennessee, and Wisconsin. The land use data are from USDA's Cropland Data Layer, a high-resolution GIS layer of crop area and other land uses through time. We combine this with geocoded refinery locations and information on each plant's capacity and year of opening. A set of 5-kilometer buffers are developed around each plant out to 75 km. Following Scott (2013), we sample land points from a grid of the region and keep all points that are located in one (or more) of the buffers. We combine the linear probability model with a difference-in-differences approach that includes point and county-year fixed effects. We use this to identify the causal effect of new ethanol capacity on the probability of a particular land use, by buffer distance. The five land uses are corn, soybeans, wheat, grassland, and developed land.

One main finding is that the probability of growing corn increases in the predicted distance-decay pattern when treated with a 1 million gallon-per-year (mgy) increase in ethanol capacity. The estimated coefficient in the first buffer, in fact, is insignificant albeit positive.[3] Thereafter, the estimated coefficients are highly significant through the 45 km buffer, at which point the effect goes to zero and remains there through the 75 km buffer. The distance-decay pattern is vivid, with the point estimates showing a relatively steady decline as distance from the plant increases. The effects are relatively small, with the probability of corn increasing by 1.6% in the 5-10 km buffer for a 100 mgy increase in capacity, a common capacity of new plants.

What land uses decrease, apparently in response to the increase in corn acreage? Here, we distinguish cultivated cropland (soybeans and wheat) versus uncultivated grassland.

[3] As described below, the probability of developed land increases in the first buffer following the treatment, suggesting that developed land may be competing successfully with corn in the immediate vicinity of the refinery.

The estimated coefficients on the respective probabilities of growing soybeans and wheat both decrease in response to the treatment. The distance-decay pattern is again clear — the negative coefficients grow smaller in absolute value as distance increases out through the 45 km buffer. Their magnitudes, in absolute value, are slightly smaller than the corn estimates, and this is reasonable. However, these coefficients are imprecisely estimated.

Grassland represents the extensive margin of cropped agriculture; it includes pasture and grass-related land cover types, all of which are uncultivated. The probability of grassland decreases in response to the treatment. With two exceptions, the estimated coefficients are statistically significant through the 50 km buffer, and the distance-decay pattern is evident in this range. Their magnitudes, in absolute value, are similar to the corn estimates. Because we study land use and not land use transition (such as a transition at a point from grassland to corn land), we cannot conclude that grassland area necessarily is being converted to corn production, yet this is the implication given that cropland in soybeans and wheat is not increasing.[4]

The second overarching research question is whether refinery openings spawn rural development. Here, the probability of developed land increases in response to treatment in the buffer adjacent to the refinery, i.e., within 5 km of the plant. The probability of developed land also increases in three rings in the 35-50 km range. This may reflect optimal spacing of ethanol refineries, although this needs further study.

This research relates to three strands of literature. First, it extends research on spatial concentration of the economy to study agglomeration in the agricultural sector. To date, agglomeration has largely been studied within the urban economy (Glaeser and Gottlieb, 2009). Yet the agricultural sector shows substantial geographic concentration and specialization within the United States, more so than most other sectors (Holmes and Stevens, 2004). Here, we show that corn ethanol refineries causally affect the intensive margin of cropland use (e.g., whether to grow corn or soybeans) and the extensive margin of converting from uncultivated to cropland. Moreover, the increase in developed land in the vicinity of refineries suggests that new plant openings might induce rural development. Whether this result corresponds to similar causal effects on rural population, employment, or enterprises merits further attention.

Second, in methodological terms, we develop a quasi-experimental approach using high resolution spatial data. Others have advocated this approach for answering spatial questions (Gibbons and Overman, 2012; Holmes, 2010). Plant openings is an especially

[4] In the first buffer, the estimated coefficient on the probability of grassland is relatively large in absolute value. As we will see in the next paragraph, grassland might also be converted to developed land in this buffer.

useful application area (Greenstone et al., 2010; Davis, 2011). In addition, as demonstrated and described previously (Duranton and Overman, 2005; Overman, 2010), high resolution spatial data create the opportunity to study distance explicitly instead of, more typically, relying on geopolitical units such as counties. Transportation costs are central to spatial economies, and our results show clearly how road-distance to the refinery affects both landowner decision-making and rural development.

Third, our research contributes to analysis of the impacts of the U.S. biofuel mandate. Under the Renewable Fuel Standard (RFS), a minimum annual volume of corn ethanol must be produced domestically for use as a transportation fuel. Recent research investigates the cropland-area response to supplying the 3.33% increase in calories from major crops (corn, rice, soybeans, and wheat) that is implied by the RFS. Roberts and Schlenker (2013) estimate that the response occurs at the extensive margin of crop area, not at the intensive margin of producing higher yields of these crops from existing area. They estimate that the mandate-induced price increase results in a 2.3% increase in cultivated land area, while Scott (2013) estimates a 2.9% increase in cultivated land area using a dynamic model. Ethanol refineries were similarly induced by the RFS mandate (Thome and Lin Lawell, 2015). Our results for the Corn Belt complement the aggregate results; the estimated distance-decay functions show how major land uses responded directly to the refineries' demand for corn feedstock to meet the RFS.

The paper continues as follows. Section 2.2 develops a model of the relationship between land use choice and transportation cost; Section 2.3 presents the data; Section 2.4 discusses the empirical model and identification strategy; Section 2.5 presents the results; Section 2.6 concludes.

2.2 A Simple Spatial Model of Land Use

Suppose that landowners choose how to allocate land between two alternatives: corn, c, and another option specified generally as b. At any time, t, landowner i must decide how to divide her total available land, L_i, such that $l_{ict} + l_{ibt} = L_i$. She makes this choice to maximize profit, which we specify as:

$$\Pi_{it} = (P_{ct} - \tau_c d_{ict}) f_c (l_{ict}, x_{ict}, w_{it}, s_i) + P_{bt} f_b (l_{ibt}, x_{ibt}, w_{it}, s_i) \tag{2.1}$$

where P_{ct} and P_{bt} are prices received for corn and good b at time t, respectively; τ_c is the transportation cost per unit of distance (d_{ict}) for moving corn to market; $f_c(\cdot)$ and $f_b(\cdot)$ are production functions defined over allocated land, l, time-varying inputs specific to the land use, x, weather, w, and time-invariant features of the land (e.g., soil) or region (e.g., transportation network), s.[5] We assume that the production functions are strictly concave with respect to land such that $\frac{\partial f}{\partial l} > 0$ and $\frac{\partial^2 f}{\partial l^2} < 0$ for both c and b. Without loss of generality, we abstract from input costs to focus on the role of transportation cost.

At an internal solution, the landowner will allocate land such that the marginal profit of the two choices are equal:

$$(P_{ct} - \tau_c d_{ict}) \frac{\partial f_c}{\partial l_c} = P_{bt} \frac{\partial f_b}{\partial l_b} \tag{2.2}$$

In this model, we are interested in how land use responds to changes in both transportation distance and corn prices. Applying the Implicit Function Theorem, we obtain:

$$dl_{ict} = \left[\frac{1}{(P_{ct} - \tau_c d_{ict}) \frac{\partial^2 f_c}{\partial l_c^2} + P_{bt} \frac{\partial^2 f_b}{\partial l_b^2}} \right] t_c \frac{\partial f_c}{\partial l_c} dd_{ict} - \frac{\partial f_c}{\partial l_c} dP_{ct} \tag{2.3}$$

where dl_{ict} is the change in corn acreage, dd_{ict} is the change in distance to market, and dP_{ct} is the change in corn price. The expression in brackets is negative, assuming that the net-prices are both positive, which must be the case for an internal solution.

Ignoring changes in the corn price to start, the model predicts that landowners will increase the amount of land devoted to corn when transportation distance decreases, as would occur if a new ethanol refinery were constructed nearby. Larger changes in distance produce larger changes in net-price, and therefore, larger changes in acreage devoted to corn.

On average, one would expect changes in transportation distance to be greater for parcels closer to new ethanol refineries. If so, the predicted change in corn acreage would be greater than or equal to zero for all parcels, but decreasing in distance from the refinery. Eventually, for points sufficiently far away, the new refinery would have no effect as other local sources of demand would be closer.

Ethanol refineries, however, can also set their own prices and will want to minimize the cost of their corn input. It is conceivable that a new refinery could strategically offset changes in transportation distance with a lower offered price of corn. Even so, evidence generally suggests that the increase in local demand from new refineries leads to increases in local prices.[6] Not surprisingly, the result in Equation (2.3) shows that price increases

[5] We leave the specification of good b general such that it could represent another crop such as soybeans, or even developed land.

[6] See, for example: Miller, E. "How Does Changing Ethanol Capacity Affect Local Basis?" (March 24, 2015) Department of Consumer and Agricultural Economics, University of Illinois Policy Matters Blog. http://policymatters.illinois.edu/author/elzbth-miller/

lead to additional increases in corn acreage.

Finally, note that the change in acreage for option b is exactly opposite the change for corn due to the land constraint. For example, if b is another crop, such as soybeans, the implication is that acreage should decrease in response to nearby refinery construction.

2.3 Data

2.3.1 Ethanol Locations

Our information on the location and production levels of U.S. ethanol plants is assembled from several sources. Between 2002 and 2012, the Renewable Fuels Association (RFA) published an annual Ethanol Industry Outlook every February that included a listing of all ethanol plants that were either operating or under construction.[7] The data includes the company name, the town and state in which the plant is located, the current capacity, and any planned expansions. The reports from 2009-2012 also include production levels, which may differ from total capacity. In some cases, a parent company with multiple plants (e.g. Archer Daniels Midland) lists total capacity for all of its plants, but not for individual plants. We use data obtained from personal correspondence with staff at Ethanol Producer Magazine to fill these holes.[8] We also used Internet news sources to check whether plants were truly operating in all years as the annual outlook may list a positive nameplate capacity for idle plants.

The RFA data does not provide street addresses for the refineries. Yet we need precise locations in order to exploit the high resolution of the Cropland Data Layer and to estimate local effects of proximity to ethanol plants. Our solution is to match the RFA list of facilities with EPA's Toxics Release Inventory (TRI) and Facility Registry System (FRS), which gives precise locations of each facility. For some plants, there is no record in the publicly available EPA data. In these cases, addresses were obtained from news releases, yellow pages, company websites, or media sources. In all cases, we are careful to map refinery locations and not administrative offices, so when possible we confirm the address using aerial imagery from Google Maps and company websites. The process is tedious since some plants went through several ownership and name changes, while others closed permanently. Our aggregated data set tracks these changes across time with a unique identifier for each plant regardless of ownership. Figure 2.1 maps all corn-based refineries across the

[7] Although the report continues to be published, beginning in 2013, the report no longer provides a listing of active plants. See the RFA website at http://www.ethanolrfa.org

[8] EPM gathers capacity information from publicly available regulatory filings (e.g. for air permits) as well as news releases and annual reports. EPM is online at http://www.ethanolproducer.com/

U.S. that operated with positive production capacity at some point between 2002 and 2012, a total of 199 plants.

2.3.2 Cropland Data Layer

The land use data comes from the Cropland Data Layer (CDL), which is produced by the National Agricultural Statistics Service (NASS) at USDA. The CDL is distributed publicly as a high-resolution raster-formatted GIS dataset. It is created from a combination of satellite imagery, ground truth data collected by USDA, and other ancillary data sources. The CDL covers all 48 contiguous states for the period 2008-2015, but there is state-by-state variation in availability prior to 2008.[9] Since the ethanol data begins in 2002 and ends in 2012, we use all available CDL data between those years, which means we have an unbalanced panel where the first observable year varies by state.

The spatial resolution also varies by year; it is 30 meters for 2010-2015 and all years prior to 2006, but it is 56 meters for the period 2007-2009. To give a sense of magnitude, the 2012 CDL (30m) contains 8.7 billion pixels and is shown in Figure 2.1. Collectively, these pixels classify 131 different land cover categories consisting of 107 major and minor crops (e.g. corn, soybeans, cherries, Christmas trees) as well as 24 non-agricultural land cover categories such as shrubland, woody wetlands, deciduous forest, developed/low, developed/medium, and developed/high intensity. NASS statistically assesses the accuracy of the agricultural land cover estimates for each CDL state and vintage. For example, the accuracy of the 2009 CDL for major crops is estimated to range between 85% and 95% (Boryan et al., 2011).

2.3.3 Sample Points for Analysis

Since the CDL is organized in raster form, a question arises as to what constitutes a sample observation for regression analysis. Previous research either uses the CDL pixels directly as observations (Scott, 2013; Wright and Wimberly, 2013) or aggregates the pixels to defined areas, such as sections from the Public Land Survey System (PLSS) (Holmes and Lee, 2012). We follow Scott (2013) and construct an 840m sub-grid of points across the contiguous U.S., extracting CDL values over time from those points. There are several reasons for selecting this grid size. First, 840 is the least common multiple of 30 and 56, the two resolutions of the CDL, meaning that an 840m grid can fit either resolution without raster cells overlapping the boundaries. Second, we "strike a balance between having a comprehensive sample of fields and artificially increasing the sample size by sampling

[9] For example, North Dakota CDL's are available back to 1997, while Michigan's first CDL is for 2007.

many points from individual fields" (Scott, 2013). For example, for land organized according to the PLSS, the quarter section is 0.5 miles or 805m per side.[10] Quarter sections are further divided into 4 fields referred to as quarter-quarter sections, each 402m per side. Thus, the grid, on average, selects one raster cell from each quarter section, or rather, from 1 out of every 4 "fields" under the PLSS.

In total, the grid produces 11,061,279 points in the contiguous U.S., of which 3,114,801 are in the Midwest states considered in this analysis.[11] For each point, we extract soil information using the publicly available gridded SSURGO database (gSSURGO) developed by the USDA Natural Resources Conservation Service.[12]

In order to identify the effect of proximity to ethanol production, we require a measure of distance between each point and the set of ethanol refineries. In practice, we do this by constructing a series of 5 km-wide rings around each refinery based on the U.S. road network. Instead of using a set of concentric circles, the rings measure actual transportation distance. As a result, they are irregularly shaped and depend on the geography of local roads. Figure 2.2a shows the difference between using a simple circle and road-based buffers for a refinery located in Albion, MI. We intersect the road rings with the grid points and thereby identify the set of ethanol plants within 75 km of each point at 5 km intervals. An example for a single 5 km-wide ring is shown in Figure 2.2b. A total of 1,411,284 points, roughly 45% of Midwest points, are within 75 km of an ethanol refinery that operated between 2002 and 2012.

Finally, we use the Protected Areas Database of the United States, produced by USGS, to identify and remove points in protected lands.[13] In the descriptive statistics and analysis that follows, we also remove points that are ever identified in the CDL as open water, perennial ice, or clouds.

2.4 Empirical Model

Since the data are structured as a set of points on a grid, we do not observe acreage, but rather a single land use or crop choice associated with the CDL value beneath each grid point. These values are used to model the decision to adopt corn as well as other crop/land-use choices as a series of binary discrete choice outcomes, much like McWilliams and

[10] The Homestead Act of 1862 allocated quarter sections for free to people. Even today, ownership patterns often vary by quarter section (Holmes and Lee, 2012).

[11] We consider IA, IL, IN, KS, KY, MI, MN, MO, ND, NE, OH, SD, TN, and WI.

[12] Information on gSSURGO is available at
http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053628

[13] Data is publicly available at http://gapanalysis.usgs.gov/padus/data/.

Moore (2016b). As such, we specify the dependent variable $Y_{itk} = 1$ if point i is associated with crop/land use k at time t, and $Y_{itk} = 0$ otherwise. With a binary dependent variable, the empirical specification aims to identify the causal effect of proximity to an ethanol refinery on the probability of land use k.

$$\begin{aligned} Y_{ikt} =& \alpha_k + \sum_r \beta_{rk} C_{irt} + \mu_{ik} + \theta_{ckt} + \epsilon_{ikt} \\ \text{where } C_{irt} =& \sum_p c_{pt} 1 \left[r - 5 < d_{ip} \leq r \right] \end{aligned} \tag{2.4}$$

Equation (2.4) is estimated using the traditional within estimator, where μ_{ik} are time-invariant point fixed effects, θ_{ckt} are county-year fixed effects, and the β terms represent the crop-level treatment effects indexed by ring r.[14] The C_{irt} represent the total capacity (or production when available) of all plants that are operating at time t and are between $r - 5$ and r km of point i, where d_{ip} represents the distance between point i and plant p and c_{pt} is the capacity of plant p at time t.

Our primary research question pertains to the agglomeration of corn around ethanol refineries, which we focus on for our discussion of identification. In this case, $k =$ "corn" and, therefore, $Y_{ikt} = 1$ when point i grows corn.

As we are using the within estimator, the treatment effects are identified only if the error in each year is uncorrelated with treatment in *all* years. That is,

$$\mathrm{E}\left(C_{irs}\epsilon_{itk}\right) = 0 \text{ for all } s, t = 1, ..., T \tag{2.5}$$

This rules out situations where investors respond to positive shocks at land point, i, by building a nearby refinery in the future. Although it is unlikely that a shock at a single point leads to this kind of investment, investors might respond to positive shocks at a collection of points when they are spatially correlated. That is, if many farms in a given region all experience positive shocks and plant more corn, this could catch the attention of investors and pave the way for new ethanol plants in the future. However, shocks such as these should be captured by the county-year fixed effects, thereby allowing the point-level errors to be strictly exogenous with respect to the treatment variables.

Another way of thinking about the required identification assumption is that the treatment variables (production capacities by ring) must be randomly assigned to points, effectively, after controlling for the point and county-year fixed effects. In other words, we have a difference-in-differences type common trends assumption that points within the same

[14] $r \in \{5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75\}$ is defined in terms of km.

county would have similar expected probabilities of growing corn if not for distance and production capacity of newly constructed refineries conditional on the time invariant point characteristics.

Identification of causal effects fails if the common trends assumption is violated, i.e. if points closer to new refineries are systematically different even after controlling for the fixed effects. For instance, ethanol refineries are generally owned by profit-maximizing firms. The locational choice problem for new plants involves a strategic component (Thome and Lin Lawell, 2015). If new refineries knowingly locate in areas, for example, where parcels within 10 km are better poised to plant new corn than parcels 30 km away, and importantly, these differences are not captured by the fixed effects, then our estimates will overstate the effect of proximity to the plant.

We argue that our fixed effects account for these concerns. First, it is likely that counties within a state are different in important ways that lead to nonparallel trends in land use. Some of this may be due to changes in population, development, or other features of local business between 2002-2012, which vary by county. Counties 40 km to the west of an ethanol plant may be very different from counties 40 km to the east. For instance, Figure 2.2b shows that the 45-50 km ring around the Andersons Albion Ethanol LLC refinery in Albion, MI intersects 8 counties. Our county-year fixed effects allow time-varying differences between these counties to exist.

Second, the point fixed effects should capture all of the factors that make land point i more suitable to growing corn than point j *in the same county*. Examples include soil quality, climate, field topology, altitude, distance to the closest river, distance to the center of town, the local transportation network, and even the pre-2002 land use histories and the managerial aspects of the owner. These are essential characteristics that constitute the natural advantages of different points.

Furthermore, the fixed effects will also account for the main drivers in locational decisions of ethanol plants. In a 2010 survey of ethanol producers, Schmidgall et al. (2010) ask what the most important factors are for site selection. Over 85% of respondents identified access to rail, highways, water, and corn as the most important. In addition, many respondents also gave importance to state and local taxes, ease of obtaining permits, as well as community support. Other research by Haddad et al. (2009) and Lambert et al. (2008) support these findings, with Haddad et al. (2009) finding natural gas availability, as measured by pipeline miles, also to be important. All of these items are controlled for with a combination of the point and county-year fixed effects. The implication is that we can consider plant location within the sample to be essentially random conditional on the fixed effects.

Our conclusion is that estimation of Equation (2.4) results in causal estimates of the effect of distance and production capacity. In the context of the four forces of agglomeration discussed earlier, factors of natural advantage are captured by the point fixed effects, while the county-year fixed effects control for changes in local labor-market pooling and knowledge spillovers. We thus identify the effects of changes in input-output linkages.

In practice, we restrict estimation of Equation (2.4) to points for which at least one year of CDL data is observable before any ethanol refinery within 75 km is operational, which emphasizes the difference-in-differences interpretation. Still, the treatment effect in any ring is identified off any changes in production capacity across the sample. Most existing refineries in 2002 that continued to operate in 2012 invested in upgraded capacity over the period. It is encouraging that results are similar when we do not remove points around existing refineries.[15]

2.5 Results

2.5.1 Descriptive Statistics

We begin this section by describing ethanol production over the sample period followed by land use trends. Across the U.S., there were 47 operating ethanol refineries in 2002. 152 new plants were constructed between 2003 and 2012 bringing the total to 199 refineries that operated for at least one year between 2002 and 2012. The locations of these refineries are depicted in Figure 2.1, which shows a clear agglomeration of refineries in the Corn Belt. Indeed, 176 of the 199 total plants (and 46 of the original 47) are in the Midwest states considered here. In total, 130 new refineries were constructed in the Midwest.

Despite this swift expansion, in some cases, plants shut down either temporarily or permanently. In fact, 9 of the 130 new refineries ceased operations during the sample period, although 8 eventually returned to production; 11 of the original 2002 plants exited during the period, 7 of which were permanent.

Figure 2.3a plots the total number of operating plants and the total production capacity for plants in the Midwest between 2002 and 2012. Although both the number of plants and total production capacity increases across all years, the most rapid increase was between 2007 and 2010, which saw the construction of 66 new plants along with a more than doubling of total capacity to over 11.3 billion gallons-per-year.

There is large variation in the production capacity of new plants, as shown in Figure 2.3b. Here, the distribution of capacity for first-year plants is plotted for each year. For

[15] Results are available by request.

example, the capacity of plants that produced for the first time in 2008 ranges between 20 and 130 mgy with an average of 68.5. As shown, the size of new plants has been increasing over time from an average of 40 in 2003 to 86 in 2012. Figure 2.3b also plots the distribution of production for existing plants in 2002. Here, several behemoth refineries drag the average up to 52 mgy. In fact, only 10 plants have capacities above 50 mgy in 2002. The median capacity is only 21 mgy. In general, plants have been getting bigger.

As ethanol production has increased, so too has corn acreage. Figure 2.4 plots aggregate land use trends between 2002 and 2012 across the Midwest. Acreages for corn, soybeans, and wheat are from official USDA survey estimates.[16] Data for grassland and developed land are from USDA's National Resources Inventory (NRI) (U.S. Department of Agriculture, 2015).

Between 2002 and 2012, corn increased by 25% from 67 to 84 million acres, driven by the RFS biofuel boom. Gains in corn appear to be partially offset by losses to soybeans until 2008, after which soybean acreage is relatively flat. Wheat made small gains until 2008, but then declined from 32 to 26 million acres in 2012. The NRI data includes a classification of "range", which contains most grassland. There is no meaningful change in aggregate range land between 2002 and 2012. Developed land, also from the NRI, shows a small increase from 33 to 35 million acres.

While the acreage estimates in Figure 2.4 help to understand aggregate trends, our primary research question concerns the spatial degree of change, and in particular, the relationship between changes in land use and proximity to ethanol production. Table 2.1 uses the grid of land points discussed in Section 2.3.3, restricting to points that are within 75 km of a refinery, and analyzes changes in average land use by distance from the refinery both before and after plant construction. This requires dropping points for which CDL is not available prior to plant openings.

It is interesting that there is not much variation in the gross amount of land use change by distance, despite differences in the shares themselves before and after refinery construction. For instance, points are classified as corn 28% of the time within 5 km of a future refinery location and 25% of the time for points between 60 and 65 km from a future site. However, both rings experience gains of +4 percentage points after refineries have been constructed. While corn sees a robust gain of 3-4% across all rings, soybeans sees changes of -1% for points within 25 km as well as points farther than 55 km. All other points see no change. Similarly, wheat increases by 1% within 10 km, but does not change in other rings.

In contrast to the aggregate NRI statistics, our measure of grassland using the CDL data

[16] Accessed 8/16/2016 using USDA NASS Quick Stats at https://quickstats.nass.usda.gov/.

shows declines of 4-5 percentage points across all rings, which is consistent with other work documenting grassland conversion in the Midwest.[17]

The results in Table 2.1 suggest very little difference in land use change based on proximity to ethanol production. However, these results are very coarse as they aggregate across varying years for each point. For example, point a in Michigan may not be within 75 km of ethanol production until 2009, while point b in Iowa receives treatment in 2004. The "Before Refinery" statistics aggregate the years 2007-2008 for point a as the Michigan CDL data begins in 2007, while the same statistic uses 2002-2003 for point b in Iowa. In the panel analysis that follows, we control for year and allow counties to have different trends over time with the county-year fixed effects.

Although the panel fixed effects will control for differences in soil quality in the regression analysis, Table 2.2 examines whether there are systematic differences across rings. Points closer to ethanol refineries tend to be slightly flatter, although the difference is qualitatively very small; slope gradients between 1 and 8 all fall into the "Gentle sloping" class (Soil Survey Division Staff, 1993). The bedrock depth is shallower for closer points, but the water table depth is relatively equal across rings. Finally, land capability class (lcc) measures the degree of soil limitations for field crops. Classes are specified by integers between 1 and 8, with higher numbers representing more severe limitations. Although points farther away from refineries have slightly higher lcc's on average, the difference is not large. Overall, we do not see striking differences in soil quality across rings. We now turn to the regression analysis.

2.5.2 Regression Analysis

As in the descriptive statistics, the regression analysis only uses points within 75 km of an ethanol refinery. The sample is further restricted to points for which CDL data are available prior to the construction of all refineries within 75 km, as discussed in Section 2.3.3. Along with dropping points that are in protected lands or are ever classified as open water, perennial ice, or clouds, the estimation sample is reduced from 1,411,284 to 648,799 points. Following Scott (2013), we also drop points that are ever classified as developed land in the regressions for corn, soybeans, and wheat. That leaves a final estimation sample of 535,805 points for the field crops, which over the 11-year sample period results in 5,057,057 total observations due to the unbalanced nature of the data.

[17] In 2014, USDA reclassified historical grass-related categories in the CDL and collapsed the "Pasture/Grass", "Grassland Herbaceous", and "Pasture/Hay" categories into a single "Grass/Pasture" classification. Therefore, our measure of grassland will include some parcels devoted to pasture or hay farming. While CDL accuracy for major crops tends to be more accurate than for grass-related categories, other research has made use of CDL grass classifications. See, for example, Wright and Wimberly (2013).

Estimates of Equation (2.4) using the standard within estimator are presented in Table 2.3 and Figure 2.5. The treatment variables represent total ethanol production capacity (mgy) across all plants that are within $(r-5)$ and r km of a given point. Since we are using binary dependent variables, which are indicators for specific crops or land uses, the coefficients are interpreted as the effect of a 1 mgy change in ethanol production capacity, $(r-5)$ to r km away, on the probability of the specified land use at the point level. Changes in capacity can occur because a new plant was constructed, or an existing plant was upgraded or closed.

Our preferred specification includes county-year fixed effects to control for time-varying local factors.[18] However, Figure 2.5a and columns (1) and (3) of Table 2.3 show that state-year fixed effects produce nearly identical results for corn. This suggests that variation in ethanol capacity by distance is driving the results, conditional on the point fixed effects, as intended.

It is common in the climate impacts literature for researchers to isolate observational units east of the 100^{th} meridian, which is the approximate border between irrigated crops in the West and rainfed crops in the East (Schlenker et al., 2005, 2006). While irrigation can be a confounder for studies investigating the effects of climate change, it should not be important in our context. There is no obvious reason why irrigated land should respond differently than nonirrigated land to transportation cost shocks associated with new ethanol production. Costs of conversion to cultivated corn may be higher in irrigated areas and may depend on factors such as water availability, but these differences should be captured by the fixed effects. Column (2) of Table 2.3 supports this reasoning by showing that results do not change when we exclude points west of the 100^{th} meridian.

Using our preferred specification with county-year fixed effects, the results for corn in column (3) and Figure 2.5a show that 1 mgy of additional capacity has a statistically significant positive effect on the probability of planting corn for points that are 5 to 45 km away. Although the result is not significant for points within 5 km, the estimated effect is positive. At 5 to 10 km, the effect is larger with a coefficient estimate of 0.00016. To put this in perspective, it is not uncommon for plants to be constructed with 100 mgy capacity. Our estimates imply that a new plant of this magnitude will increase the probability of growing corn by 1.6%. This effect decays to zero as distance from the plant increases, which is consistent with predictions based on the simple model in Section 2.2.

The model also predicts that a new plant will lead to decreases in competing land uses. Figure 2.5b and column (4) of Table 2.3 report the results for soybeans, which show the

[18] The current version of this paper uses state-year fixed effects for the wheat and developed land regressions. This is temporary as we await results from the computationally intensive county-year regressions.

expected opposite effect compared to corn. Points closer to new ethanol production become less likely to plant soybeans, and the estimates approach zero at distances between 45 and 50 km. Unlike corn, these estimates are smaller in magnitude, in absolute value, and are generally not significant. However, not all points that convert to corn are coming from soybeans, and those that do are likely making rotational substitutions, e.g. transitioning from the common corn-soybeans rotation to a corn-corn-soybeans rotation. If so, we should expect to see both smaller magnitudes, in absolute value, and larger standard errors than for corn.

The estimates for wheat, in column (5), are qualitatively similar to soybeans, but the effects are smaller in magnitude, and the standard errors are larger, at least for distances less than 45 km. This is not surprising as wheat occupies a much smaller share of production in the sample region, as shown in Table 2.1, and the sample is not restricted in any way to points that grow wheat prior to refinery construction. Still, the estimates provide weak evidence that the probability of wheat decreases within 40-45 km of a new ethanol refinery.

We now discuss our results involving the non-cultivated land uses: grassland and developed land. When non-cultivated land such as grassland or forest is converted into cropland, carbon is released from the plants and soil. This fact has led researchers to ask whether biofuel policy, and the resulting higher crop prices, have led to increased grassland conversion (Wright and Wimberly, 2013) and what effect this has on global greenhouse gas emissions (Searchinger et al., 2008). In a sense, these studies implicitly focus on the overall price incentive that results from RFS. Our work, in contrast, controls for local price trends with county-year fixed effects, thereby isolating the local spatial effects of refinery location. In other words, previous research focuses on *indirect* land use change, while our work identifies *direct* land use change.

We use the same linear probability model and within estimator for grassland, but here we restrict to points that are identified as grassland prior to the construction of all refineries within 75 km.[19] Thus, the model estimates the probability that grassland existing before ethanol production is not converted to other uses. Results are presented in Figure 2.5d and column (6) of Table 2.3.

As with soybeans and wheat, the results are consistent with the simple land use model and suggest that grassland is more likely to be converted when it is closer to the refinery. The point estimates are significant for 8 of the 10 distance bins from 0 to 50 km, all of which are negative and larger, in absolute value, than any of the other regressions. The estimates suggest that a new 100 mgy refinery would lead to an increase in the probability

[19]The same restriction does not make sense for field crops due to the fact that most crops are grown in a rotation.

of grassland conversion of approximately 5% within 5 km and between 2 and 2.5% for points 5 to 35 km away. Thereafter, the effect decays to zero at 50 km.

A question that arises is whether points classified as grassland are actually enrolled in the Conservation Reserve Program (CRP). If so, a particular point would be restricted from converting to other uses for the duration of the CRP contract, causing the estimates to be biased downward. In this case, the estimates could be thought of as a lower bound.

The final land use that we consider is developed land, which involves a qualitatively different research question. With a new ethanol refinery, we expect to see increases in corn and decreases in other field crops and grassland. Developed land, on the other hand, rarely converts to other uses (U.S. Department of Agriculture, 2015). The construction of an ethanol refinery can be seen as an investment in the local economy. The question is whether this investment leads to positive spillovers and agglomeration of further rural development. To test this question, we restrict to land points that are *not* classified as developed land before the first year of ethanol production.[20] The coefficient estimates in column (6) of Table 2.3 and Figure 2.5e, therefore, represent the estimated probability of non-developed land being developed as a function of ethanol production capacity by distance.

In this case, new capacity within 5 km has a positive and statistically significant effect on the probability of land being developed. Using the same extrapolation, a new 100 mgy refinery would increase the probability of development by 1%. The estimation sample drops points that are identified as developed land prior to official refinery operation. Therefore, we can rule out the plants themselves as the source of new development since a plant should be counted as developed land by the CDL in the year before its first year of operation.[21] Beyond 5 km, estimated coefficients are small and generally not statistically significant. An exception is the 35 to 45 range, which could represent other ethanol refineries, i.e. strategic locations or optimal spacing of ethanol refineries. We will continue to research this question.

It is interesting that the regressions for grassland and all of the field crops display at least weak evidence of a distance-decay relationship, while there is no such evidence from the simple average changes calculated in Table 2.1. Why is that the case? One explanation could be that large changes in commodity prices are driving broad land-use trends more than shocks to transportation cost. Table 2.1 does not control for time or local trends. In contrast, the regression fixed effects allow local prices to vary over time. When price is

[20] We denote a point as developed land if it has the CDL classification of "Developed" prior to 2007, or "low-", "medium-", or "high-intensity development" beginning in 2005.

[21] Kaplow (2007) notes that construction of a corn ethanol plant typically takes 12 months, and that a production bottleneck around 2007 extended this to 18-24 months. Future research will address this assumption by omitting a smaller buffer around the actual plant site from the current 0 to 5 km buffer.

then controlled for in the regressions, a distance-decay relationship is visible. The implied magnitudes of change from the regressions are smaller, on average, than the changes in Table 2.1, which also supports this hypothesis.

One common trait across all the regressions is that standard errors start large and get smaller as one moves farther away from the plant, regardless of the dependent variable. This is simply due to geometry and the fact that there are more observations (equally spaced points) in each 5 km ring as distance increases.

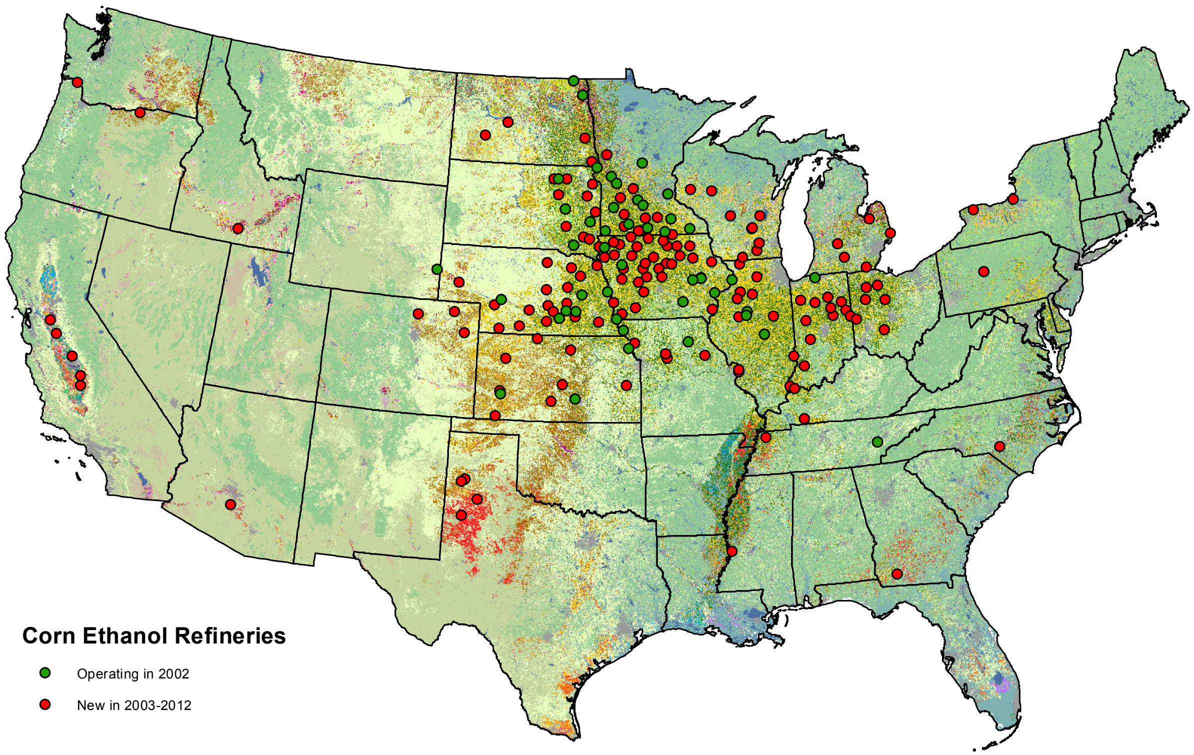
2.6 Conclusion

This paper makes two contributions to the literature. We expand the purview of agglomeration economies into the agricultural and rural economy. Holmes and Stevens (2004) report several descriptive measures of patterns of regional specialization, such as locational quotient, locational Gini coefficient, and Ellison-Glaeser index. These measures show that the agricultural production and processing sectors have a substantial amount of regional specialization, and that rural areas now specialize in manufacturing in contrast to earlier periods when it was an urban activity. We show several backward linkages from corn ethanol refining to land use. Showing the importance of transportation costs in spatial economies with immobile land, clear distance-decay patterns were estimated for corn, soybeans, wheat, and grassland in response to refinery openings. This relies on the notion of input-output linkages as an underpinning of agglomeration. In addition, ethanol plants also induced an increase in the probability of developed land in the buffer adjacent to the plant. This component of the research warrants further investigation to understand whether these plants spawned rural development in the form of population, employment, and enterprises in addition to land use.

The second contribution is to estimate the direct land-use changes of the RFS biofuel mandate. Beginning with Searchinger et al. (2008), substantial attention has focused on the indirect land-use changes (operating through crop price increases) of large biofuel mandates and their related environmental consequences. In the same vein, Roberts and Schlenker (2013) and Scott (2013) estimate that the U.S. biofuel mandate will increase acreage in major crops by 2.3% and 2.9%, respectively; this translates into 36 million acres. Focusing on land-use change in the Midwest, Wright and Wimberly (2013) document conversion from grassland to corn-soybean cropping in the western Corn Belt during 2006-2011. They attribute the change to the rapid increases in corn and soybean prices during the period, although causal estimates are not developed.

Our results, in contrast, isolate direct land-use changes caused by corn ethanol refinery openings in fourteen states encompassing the greater Midwest. The plant openings link directly to the RFS (Thome and Lin Lawell, 2015), and our results identify the plant opening effect while abstracting from national crop price effects. Hill et al. (2009) assume that the corn feedstock for expanded U.S. ethanol production would come from converted perennial grasslands. Our finding of statistically significant decreases in the probability of grasslands lends support for this.

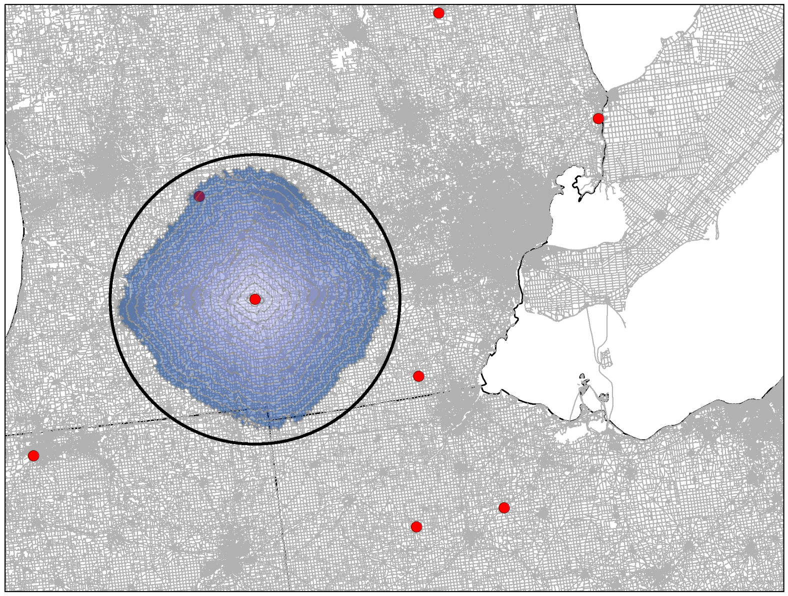
Figure 2.1: Operating Corn Ethanol Refineries in the United States, 2002-2012



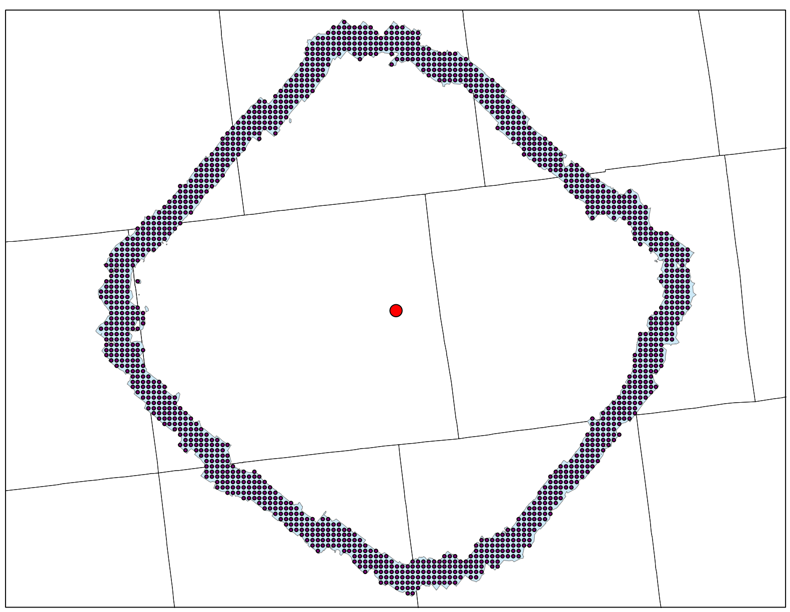
Notes: This figure maps corn ethanol plants that operated at any point between 2002 and 2012 with positive production capacity. Green dots are plants that already existed in 2002, while red dots are new plants that began production between 2003 and 2012. The background is the 2012 Cropland Data Layer at 30m resolution. Corn pixels are represented as yellow.

Figure 2.2: Proximity to Ethanol Refineries: Allocating Land Points to Buffers

(a) Comparison of a road-based buffer to a simple circle



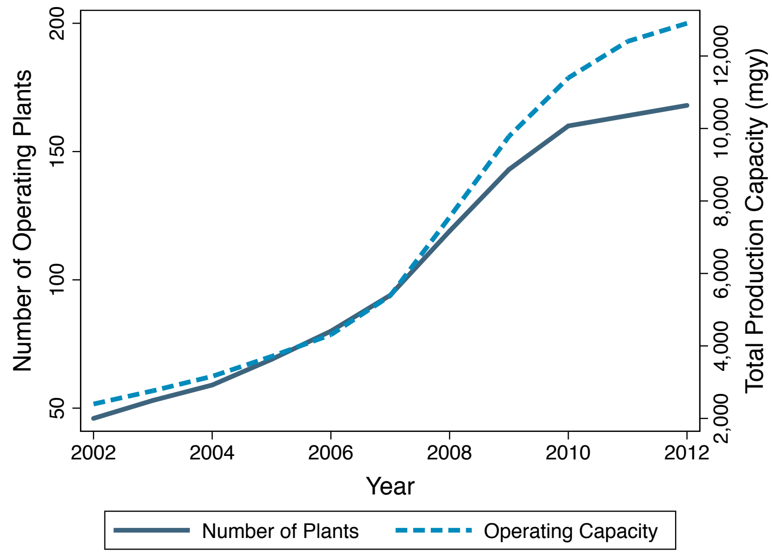
(b) Grid points within a road-based buffer



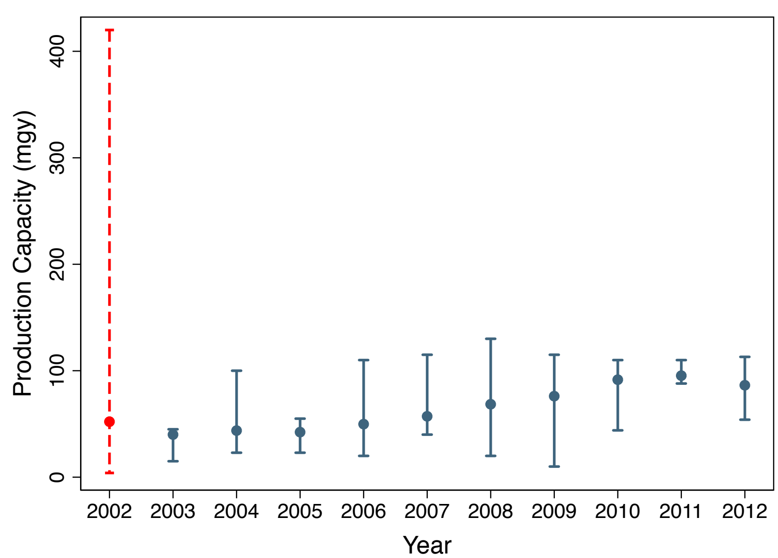
Notes: Figure (a) compares a simple circle with radius 75 km with a series of 5 km-wide road-based "rings" from 5 km to 75 km. Red dots represent ethanol refineries, while the small gray lines are roads. The buffers have been drawn around the Andersons Albion Ethanol LLC plant in Albion, MI. Figure (b) shows the set of 840m spaced grid points that are between 45 and 50 km from the same refinery in Albion, MI.

Figure 2.3: Ethanol Production in the Midwest

(a) Number of operating ethanol plants & total production capacity (mgy)

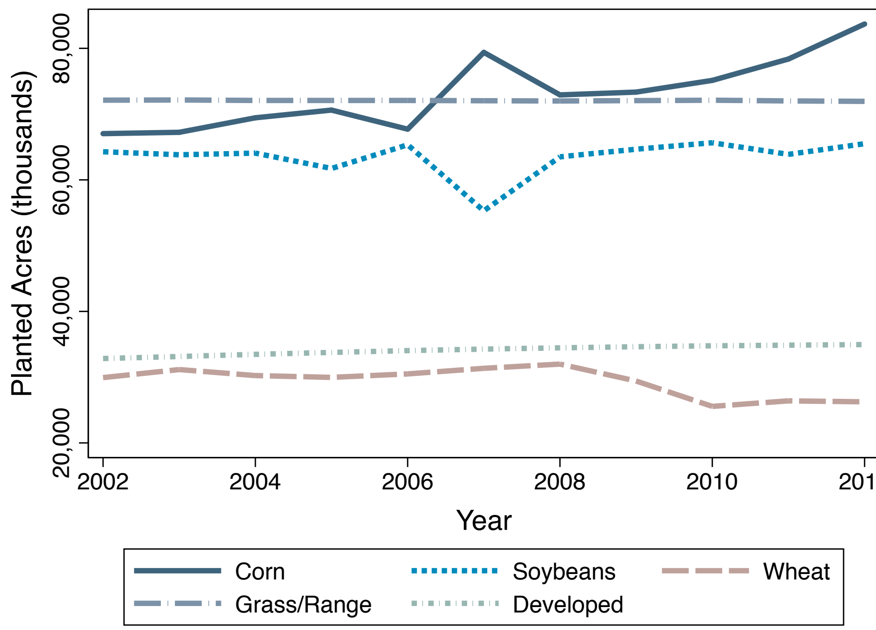


(b) Distribution of new production capacity by year



Notes: Panel (a) plots the number of operating ethanol plants and the corresponding production capacity between 2002 and 2012 for the states of IA, IL, IN, KS, KY, MI, MN, MO, ND, NE, OH, SD, TN, and WI. Panel (b) plots the distribution of production capacity across the same states for new plants in their first year of operation for each year in the sample. This is compared to the distribution of production capacity among the 46 original refineries in 2002. For all years, the dot represents the average, and the lines represent the range between minimum and maximum capacity.

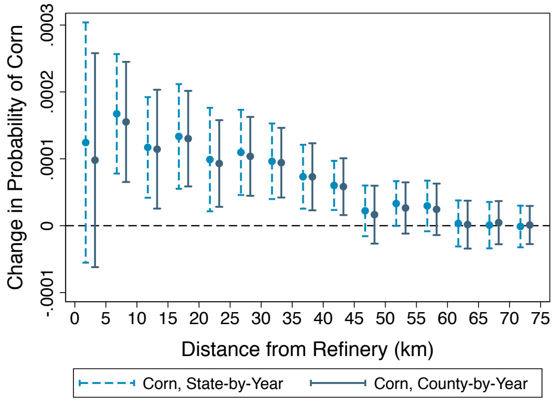
Figure 2.4: Total Midwest Acreage: Corn, Soybean, Wheat, Grass, & Developed Land (Thousands of Acres)



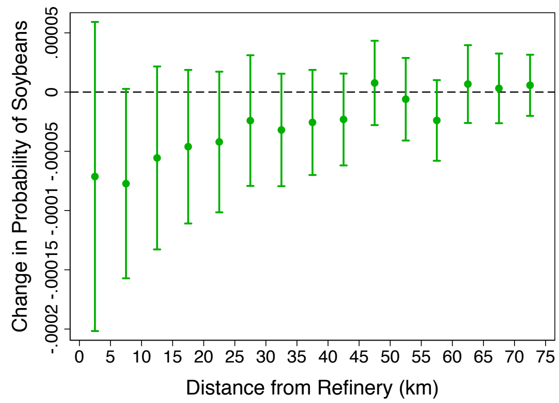
Notes: This figure plots the total acreage (1000's) across each of the states considered in our analysis: IA, IL, IN, KS, KY, MI, MN, MO, ND, NE, OH, SD, TN, and WI. Acreage for corn, soybeans, and wheat were obtained from USDA survey data (accessed 8/16/2016 using USDA NASS Quick Stats at https://quickstats.nass.usda.gov/). Wheat represents the combination of winter wheat, spring wheat, and durum wheat. Data for grassland and developed land acreage comes from USDA's National Resources Inventory (U.S. Department of Agriculture, 2015). In the NRI data, the range category includes grasslands, savannas, tundra, some wetlands, and deserts.

Figure 2.5: Estimated Probability of Different Land Uses by Distance from Refinery

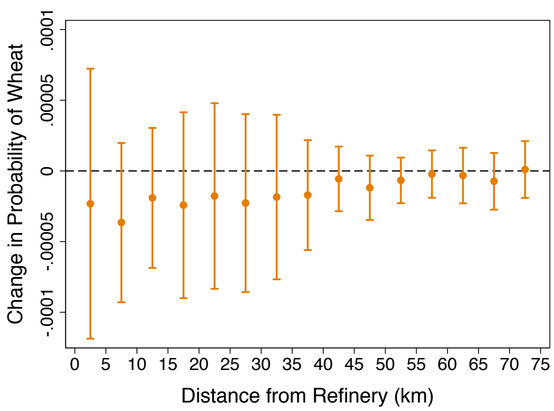
(a) Corn Regressions



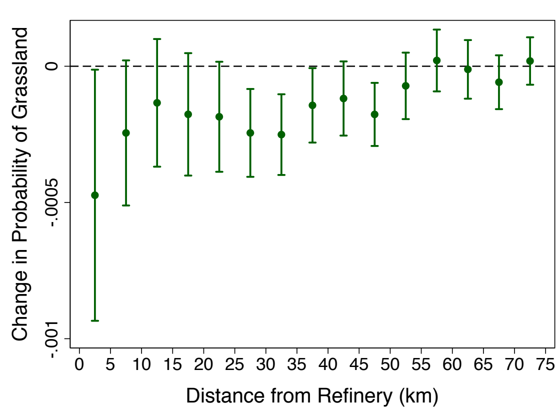
(b) Soybeans with county-by-year FE's



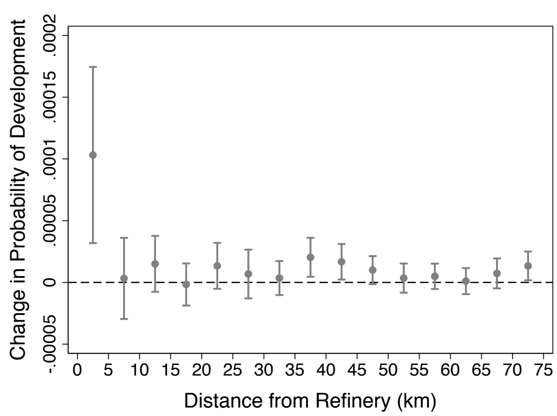
(c) Wheat with state-by-year FE's



(d) Grassland with county-by-year FE's



(e) Developed Land with state-by-year FE's



Notes: This figure plots the estimated coefficients from Table 2.3 with 95% confidence intervals. Estimates can be interpreted as the change in the probability of the given land use for a 1 mgy increase in ethanol production at the specified distance.

Table 2.1: Land Use Change by Ring of Distance from Ethanol Production

	Before Refinery					After Refinery					Change				
Distance	Corn	Soy	Wheat	Grass	Dev	Corn	Soy	Wheat	Grass	Dev	Corn	Soy	Wheat	Grass	Dev
$(0, 5]$	0.28	0.23	0.03	0.22	0.07	0.32	0.22	0.04	0.18	0.06	0.04	-0.01	0.01	-0.04	-0.01
$(5, 10]$	0.30	0.24	0.04	0.22	0.04	0.33	0.23	0.04	0.18	0.04	0.03	-0.01	0.01	-0.04	-0.01
$(10, 15]$	0.30	0.24	0.04	0.23	0.03	0.33	0.24	0.04	0.18	0.03	0.04	-0.01	0.00	-0.04	0.00
$(15, 20]$	0.29	0.25	0.04	0.23	0.03	0.33	0.24	0.04	0.19	0.03	0.03	-0.01	0.00	-0.04	-0.01
$(20, 25]$	0.29	0.24	0.03	0.23	0.04	0.32	0.24	0.04	0.19	0.03	0.04	-0.01	0.00	-0.05	-0.01
$(25, 30]$	0.28	0.24	0.03	0.24	0.03	0.32	0.24	0.03	0.19	0.03	0.04	0.00	0.00	-0.05	-0.01
$(30, 35]$	0.28	0.24	0.03	0.25	0.03	0.32	0.24	0.03	0.20	0.03	0.04	0.00	0.00	-0.05	-0.01
$(35, 40]$	0.27	0.23	0.03	0.25	0.03	0.31	0.23	0.03	0.20	0.03	0.04	0.00	0.00	-0.06	0.00
$(40, 45]$	0.27	0.23	0.03	0.26	0.03	0.31	0.23	0.03	0.20	0.03	0.04	0.00	0.00	-0.05	0.00
$(45, 50]$	0.26	0.23	0.03	0.26	0.03	0.31	0.23	0.03	0.21	0.02	0.04	0.00	0.00	-0.05	0.00
$(50, 55]$	0.26	0.23	0.03	0.26	0.03	0.30	0.23	0.03	0.21	0.03	0.04	0.00	0.00	-0.05	-0.01
$(55, 60]$	0.26	0.23	0.03	0.26	0.04	0.29	0.22	0.03	0.22	0.03	0.04	-0.01	0.00	-0.04	-0.01
$(60, 65]$	0.25	0.22	0.03	0.27	0.04	0.29	0.22	0.03	0.22	0.03	0.04	-0.01	0.00	-0.05	-0.01
$(65, 70]$	0.25	0.22	0.03	0.27	0.04	0.28	0.21	0.03	0.23	0.03	0.03	-0.01	0.00	-0.04	0.00
$(70, 75]$	0.25	0.22	0.03	0.26	0.04	0.28	0.21	0.04	0.22	0.04	0.03	-0.01	0.00	-0.04	0.00

Notes: This table reports the average percentage of time (years) that land points are classified as corn, soybeans, wheat, grass, or developed land in the CDL, both before and after ethanol production began and by ring of distance from ethanol production. Points are only used if they are observed both before and after the opening of each refinery within 75 km. Distances are specified as $(l, u]$, which includes all points within l and u km of ethanol production. The wheat category represents the combination of winter, spring, and durum wheat varieties; Grass is defined by the CDL category "Grass/Pasture"; Developed land is classified as either "Developed" prior to 2007 or low-, medium-, or high-intensity development beginning in 2005.

Table 2.2: Average Soil Quality by Ring of Distance from Ethanol Production

Distance	Slope Gradient	Bedrock Depth	Water Table Depth	Land Capability Class
$(0, 5]$	3.52	2.15	29.56	2.69
$(5, 10]$	3.94	2.31	28.95	2.75
$(10, 15]$	4.07	2.53	29.28	2.75
$(15, 20]$	4.20	2.72	28.84	2.76
$(20, 25]$	4.31	2.81	29.09	2.77
$(25, 30]$	4.42	2.80	29.11	2.78
$(30, 35]$	4.45	2.91	28.91	2.79
$(35, 40]$	4.53	2.99	28.69	2.81
$(40, 45]$	4.55	3.02	29.09	2.82
$(45, 50]$	4.58	2.96	28.86	2.82
$(50, 55]$	4.65	3.08	28.90	2.83
$(55, 60]$	4.73	3.21	28.78	2.84
$(60, 65]$	4.81	3.44	29.19	2.85
$(65, 70]$	4.83	3.60	29.21	2.85
$(70, 75]$	4.78	3.66	29.32	2.83

Notes: This table reports average soil characteristics of land points by ring of distance from the ethanol refineries. Distances are specified as $(l, u]$, which includes all points within l and u km of ethanol production. The soil data is obtained from the publicly available gridded SSURGO database (gSSURGO) developed by the USDA Natural Resources Conservation Service.

Table 2.3: Linear Probability Model Estimates of Land Use, 2002-2012

	Corn (1)	Corn E100 (2)	Corn (3)	Soybeans (4)	Wheat (5)	Grass (6)	Developed (7)
$(0, 5]$	0.00012	0.00013	0.00010	-0.00007	-0.00002	-0.00047**	0.00010***
	(0.00009)	(0.00009)	(0.00008)	(0.00007)	(0.00005)	(0.00023)	(0.00004)
$(5, 10]$	0.00017***	0.00017***	0.00016***	-0.00008*	-0.00004	-0.00024*	0.00000
	(0.00005)	(0.00005)	(0.00005)	(0.00004)	(0.00003)	(0.00014)	(0.00002)
$(10, 15]$	0.00012***	0.00010**	0.00011**	-0.00006	-0.00002	-0.00013	0.00002
	(0.00004)	(0.00004)	(0.00005)	(0.00004)	(0.00003)	(0.00012)	(0.00001)
$(15, 20]$	0.00013***	0.00013***	0.00013***	-0.00005	-0.00002	-0.00018	0.00000
	(0.00004)	(0.00003)	(0.00004)	(0.00003)	(0.00003)	(0.00011)	(0.00001)
$(20, 25]$	0.00010**	0.00009***	0.00009***	-0.00004	-0.00002	-0.00019*	0.00001
	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00010)	(0.00001)
$(25, 30]$	0.00011***	0.00011***	0.00010***	-0.00002	-0.00002	-0.00024***	0.00001
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00008)	(0.00001)
$(30, 35]$	0.00010***	0.00010***	0.00009***	-0.00003	-0.00002	-0.00025***	0.00000
	(0.00003)	(0.00002)	(0.00003)	(0.00002)	(0.00003)	(0.00008)	(0.00001)
$(35, 40]$	0.00007***	0.00007***	0.00007***	-0.00003	-0.00002	-0.00014**	0.00002**
	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00002)	(0.00007)	(0.00001)
$(40, 45]$	0.00006***	0.00006***	0.00006***	-0.00002	-0.00001	-0.00012*	0.00002**
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00007)	(0.00001)
$(45, 50]$	0.00002	0.00002	0.00002	0.00001	-0.00001	-0.00018***	0.00001*
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00006)	(0.00001)
$(50, 55]$	0.00003*	0.00003*	0.00003	-0.00001	-0.00001	-0.00007	0.00000
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00006)	(0.00001)
$(55, 60]$	0.00003	0.00003*	0.00002	-0.00002	0.00000	0.00002	0.00000
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00006)	(0.00001)
$(60, 65]$	0.00000	0.00001	0.00000	0.00001	0.00000	-0.00001	0.00000
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00005)	(0.00001)
$(65, 70]$	0.00000	0.00000	0.00000	0.00000	-0.00001	-0.00006	0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00005)	(0.00001)
$(70, 75]$	0.00000	0.00000	0.00000	0.00001	0.00000	0.00002	0.00001**
	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00004)	(0.00001)
FE	State-Yr	State-Yr	County-Yr	County-Yr	State-Yr	County-Yr	State-Yr
N	5,057,057	4,385,129	5,057,057	5,057,057	5,057,057	1,483,482	5,916,561
Points	535,805	470,372	535,805	535,805	535,805	154,910	625,315
R^2	0.0065	0.007	0.012	0.008	0.003	0.23	0.017

Notes: This table reports regression results using the linear probability model and the within-estimator. The dependent variable is given by the column. "Corn-E100" represents a sample restricted to points east of the 100^{th} meridian. The "Grass" regressions restrict to points that were classified as grass in the first observable year of CDL data. The "Developed" regressions drop all points that are classified as developed prior to the first year of ethanol production. The regressions also restrict to points for which at least one year of CDL is observable before any ethanol refinery within 75 km is operational. The treatment variables are total operational capacity of all ethanol refineries within l and u km and are represented in the table as $(l, u]$. Estimates can be interpreted as the change in the probability of the given land use for a 1 mgy increase in ethanol production at the specified distance. Regressions all include a constant in addition to the fixed-effects specified by the column. Standard errors are clustered by county. Asterisks designate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

CHAPTER 3

The Strategic Effects of Adapting to Climate Change (and Letting Others Mitigate)

3.1 Introduction

While the public continues to debate climate policy and whether humans should be held responsible for climate change, the general scientific consensus is that the earth is warming regardless of the cause. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), released in 2013, predicts a "likely" global average temperature increase in the range of $0.3 - 4.8\,^{\circ}\mathrm{C}$ over the next century (IPCC, 2013). The consensus maintains that at least some of this increase can be prevented by reducing emissions and atmospheric concentrations of greenhouse gases. In this spirit, the majority of research and policy attention has attempted to identify the most efficient of such mitigation strategies.

However, current emissions combined with the inertia of the global climate system lead many to acknowledge that some degree of warming is unavoidable. As temperatures rise, society will be forced to adapt to new conditions, causing shifts in agricultural practices, coastal development, water management, and even the distribution of labor.

At a general level, there are two distinct types of strategies to defend against climate change: mitigation and adaptation. Mitigation (or abatement) strategies will reduce the scale and likelihood of adverse climate effects; adaptation strategies will lessen the impacts. Each strategy has different implications for global welfare. While all countries can benefit from reductions in emissions, adaptation only benefits the country making the investment. Thus, the freeriding incentive is clear: adapt and let others reduce emissions.

This chapter is co-authored with Stephen W. Salant. I would like to thank Michael Moore, Ryan Kellogg, Shaun McRae, Robyn Meeks, and participants at the 2009 Heartland Environmental and Resource Economics Workshop at the University of Illinois at Urbana-Champaign for helpful comments.

Research on adaptation to climate change has been increasing, although more work is needed to understand the multitude of adaptive responses and how to incorporate them into existing models (Burke et al., 2016). Most of the early work in this area is either qualitative or highly empirical in nature, such as impact assessments.[1] Recent advances also tend to be empirical, focusing on observed behavior and how agents have adapted to climate change that has already occurred.[2] This paper, however, focuses on game theory.

The existence of multiple autonomous players with conflicting interests and heterogenous payoffs makes climate change an interesting topic for game-theoretic modeling. The application of game theory to climate change and transboundary pollution, in general, has a well established literature. Traditional games, such as Hoel (1991), ignore adaptation as a possible strategy and focus exclusively on mitigation.[3] However, studies are beginning to add adaptation to these games.

Our work is most related to Ebert and Welsch (2011), Ebert and Welsch (2012), and Eisenack and Kähler (2016). Ebert and Welsch (2011) combines mitigation and adaptation in a simple two-country game and shows how it is possible to get emissions best-response curves (to foreign emissions) that are upward-sloping when adaptation is included, i.e. emissions become strategic complements. Ebert and Welsch (2012) continues with the same model and derives comparative statics in Nash Equilibrium describing how emissions, adaptation, and to some degree, welfare responds to changes in parameters governing the effectiveness of adaptation and the benefits and damages associated with pollution.

Eisenack and Kähler (2016) builds off the Ebert and Welsch models, but reframes it as a Stackelberg game, examining whether adaptation provides any new incentives for unilateral (first-mover) action in either adaptation or mitigation. They find that conditions continue to hold where adaptation leads to strategic complements in emissions. Furthermore, equilibria in the Stackelberg setting are Pareto-superior to the standard noncooperative solution in a static game, suggesting that unilateral action can be profitable.

Other researchers have developed games combining adaptation and mitigation to study a range of other topics. For example, Zehaie (2009), Buob and Stephan (2013), and Buob and Stephan (2011) all focus to some extent on the temporal differences inherent to mitigation and adaptation strategies; the benefits from mitigation may not be realized for years,

[1]Empirical studies include Yohe et al. (1995), Yohe et al. (1996), Tol et al. (1998), Sohngen et al. (2001), Nicholls (2004), Alberth and Hope (2007), Seo and Mendelsohn (2008), and Mansur et al. (2008). Nice qualitative discussions can be found in Fankhauser et al. (1999), and Tol (2005).

[2]Examples include studies of the impact of climate on: household preferences and location choice (Albouy et al., 2016), the use of air conditioning (Davis and Gertler, 2015), agricultural yield (Burke and Emerick, 2016), and land use choice (McWilliams and Moore, 2016b).

[3]Examples of other mitigation-only climate games include Hoel (1992), Missfeldt (1999), Helm (2003), Kemfert et al. (2004), Forgo et al. (2005), and Asheim et al. (2006).

while benefits from adaptation can often be realized immediately. For example, Zehaie (2009) focuses on the order of adaptation and mitigation choices and the question of when investments in adaptation can be used strategically to elicit greater mitigation from rivals.

Buob and Stephan (2013) analyze when it is optimal for developed countries to fund the adaptation of developing countries, where adaptation funding decisions are chosen before mitigation in a 2-stage game. On the other hand, Buob and Stephan (2011) forces countries to chose mitigation in advance of adaptation and explores the optimal mitigation and adaptation arrangement when countries have different levels of income and exposures to climate change.

Mendelsohn (2000) offers a unique analysis of efficient adaptation in different domestic contexts, in particular the implications of private versus joint adaptation, e.g. across industries and government arenas. However, since the paper focuses on adaptation responses within a single country, there is no international component and thus, the strategic relationship with mitigation is not modeled.

Another set of papers, Kane and Shogren (2000) and Settle et al. (2007), consider mitigation and adaptation within endogenous risk frameworks, examining the changes in mitigation and adaptation in response to increased climate variability and catastrophic risk. Settle et al. (2007) also extends the model to a dynamic setting.

In the literature cited above, the emphasis typically falls on the arrangement of adaptation and/or mitigation in the economy, addressing important questions about how the ability to adapt changes the incentive to mitigate and the implications for international negotiations. However, there are other important questions regarding the actual payoff effects of the mitigation/adaptation trade-off that arise from increased abilities to adapt. That is, in a game theoretic setting, how does the ability to adapt affect payoffs relative to situations in which adaptation is restricted? To our knowledge, this question has not been addressed until now.

The theory of global public goods generally implies that mitigation will be undersupplied in any Nash equilibrium, while adaptation, as a private substitute, will be oversupplied. Most proposed solutions aim directly at mitigation by seeking to internalize externalities, either by establishing property rights, using subsidies, or by attempting to facilitate international cooperation on emissions reduction. Adaptation is usually a secondary concern, perhaps because it does not seem to pose any strategic issues. A country which invests in adaptation bears the full cost, but also receives the full benefit of its actions. This is seemingly an internal affair, not the business of the international community.

In fact, however, mitigation and adaptation are substitutes. Hence, a country which invests heavily in adaptation may scale back its mitigation efforts. In withdrawing the benefits of mitigation from other members of the international community, the country which adapts inadvertently injures them. If other countries do nothing in response, they sustain warmer temperatures than otherwise. If they mitigate more (or adapt more) they incur additional costs.

This leads us to ask whether adaptation is always beneficial once we have accounted for the strategic effects. Is it possible that adaptation constraints, taxes, or even negative shocks to marginal benefits, might result in preferred outcomes as countries substitute with mitigation? We analyze this question in the context of a simple two-country game.

When countries are symmetric, we find that a range of such payoff-increasing adjustments will always exist, relative to the original Nash equilibrium. With heterogeneous countries, on the other hand, payoff-increasing intervals exist whenever foreign mitigation increases. We begin by presenting a simple numerical example of this result.

3.2 A Numerical Example

Consider two identical countries, H and F, that have the ability to invest in both mitigation, m, and adaptation, a, in response to climate change. As a simple example, suppose that payoffs for $i = H, F$ are given by

$$\Pi^i = 2\left[230 - (m^i + m^{-i})\right](m^i + m^{-i}) + (200 - a^i)a^i - 2(m^i + m^{-i})a^i - (m^i)^2 - (a^i)^2 \quad (3.1)$$

The Nash equilibrium is easily solved by hand, yielding $m^i = 45$, $a^i = 5$, and $\Pi^i = 23,225$ for all i.

Now consider what happens if adaptation is constrained to be zero in both countries. In this case, countries can only optimize with respect to mitigation. In the Nash equilibrium of this constrained game, $m^i = 46$, $a^i = 0$, and $\Pi^i = 23,276$. Even though countries have lost the ability to optimize with respect to one of their action variables, the end result is increased payoffs. Both countries substitute mitigation for adaptation, and the benefit of greater foreign mitigation outweighs the loss from not being able to adapt. Note that a per-unit tax on adaptation with lump-sum refunds can produce identical results to the explicit constraint.[4]

Drawing on Bulow et al. (1985), we can achieve a similar result by considering changes in the marginal benefit of adaptation. In the simple unconstrained example, suppose that the marginal benefit of adaptation decreases for both countries by 8 units at all points in the $(m^i + m^{-i}, a^i)$ plane. We can accomplish this by adding the term $-8a^i$ to the expression

[4]For example, the simple result above can be replicated with a per-unit tax on adaptation of $t = 16$.

for Π^i in equation (3.1). If foreign mitigation is held constant, then home payoffs must fall with the introduction of this term. However, countries behave strategically in this game. If the foreign country also experiences the shock and substitutes for adaptation with greater mitigation, then the burden on the home country is reduced. In fact, payoffs may rise if the benefit from increased foreign mitigation is greater than the loss from the adaptation shock. Indeed, in the Nash equilibrium of this modified game, $m^i = 45.5$, $a^i = 2.5$, and payoffs rise to $\Pi^i = 23,240.25$ for all i.

In each example above, the key to the result is the substitute nature of adaptation and mitigation—a country which faces a reduced return (or explicit constraint) on adaptation will scale up its mitigative efforts. This benefits all other countries, allowing them to reduce their own expenditures. In what follows, we analyze these simple results in greater detail, deriving general conditions necessary for increased payoffs. To begin, however, we must introduce and discuss the assumptions and mechanics of the general model.

3.3 The Basic Game with Adaptation

The traditional climate change game, as represented by Hoel (1991), consists of two countries, $i = H, F$, making decisions over how much to reduce emissions, $m^i \geq 0$, with foreign mitigation given by m^{-i}. Countries are assumed to have heterogenous benefit and cost functions, $B^i(m^i + m^{-i})$ and $C^i(m^i)$, with payoffs defined as

$$\Pi^i(m^i, m^{-i}) = B^i(m^i + m^{-i}) - C^i(m^i), \quad i = H, F \tag{3.2}$$

where the uniform-mixing property of greenhouse gases implies that the benefits of a unit of mitigation are independent of the source.

To incorporate adaptation as a strategic choice variable, we redefine the benefit function of Hoel (1991) as a joint function of both global mitigation and private adaptation, $B^i(m^i + m^{-i}, a^i)$, where a^i is adaptation in country i. The costs of adaptation are assumed to be additively separable from the costs of mitigation, and are denoted $K^i(a^i)$. Thus, the payoff function with adaptation becomes

$$\Pi^i(m^i, m^{-i}, a^i) = B^i(m^i + m^{-i}, a^i) - C^i(m^i) - K^i(a^i), \quad i = H, F \tag{3.3}$$

The objective of each country is to maximize Π^i in equation (3.3) by optimally choosing the level of adaptation, a^i, and own emissions abatement, m^i, taking foreign mitigation as given. We make the following assumptions, in part to assure that sufficient conditions for a unique global maximum are met. Note that superscripts are used to index country, $i = H, F$, while subscripts will indicate the argument of differentiation (when necessary) for each function.

Assumption 1 *Levels of adaptation and mitigation must be greater than or equal to zero.*

$$m^i \geq 0$$
$$a^i \geq 0$$

Assumption 2 *The benefit functions, $B^i(m^i + m^{-i}, a^i)$, are twice continuously differentiable and strictly concave with respect to aggregate mitigation, $m^i + m^{-i}$, and home country adaptation, a^i, for all values of $m^i + m^{-i} \geq 0$ and $a^i \geq 0$. The signs of the first-order, second-order, and cross-partial derivatives obey*

$$\begin{aligned} &B_1^i > 0, \quad B_2^i > 0 \\ &B_{11}^i < 0, \quad B_{22}^i < 0, \quad B_{12}^i < 0 \quad \forall\, m^H + m^F \geq 0,\, a^i \geq 0 \end{aligned}$$

Strict concavity implies that the second-order derivatives in the Hessian satisfy

$$B_{11}^i B_{22}^i > \left(B_{12}^i\right)^2 \;\forall\, m^H + m^F \geq 0,\, a^i \geq 0$$

Assumption 3 *The cost functions are twice continuously differentiable and strictly convex for all $m^i, a^i \geq 0$, with first-order and second-order derivatives*

$$\begin{aligned} &C_1^i(m^i) > 0, \quad C_{11}^i(m^i) > 0 \quad \forall\, m^i > 0, \\ &K_1^i(a^i) > 0, \quad K_{11}^i(a^i) > 0 \quad \forall\, a^i > 0, \\ &C_1^i(0) = 0 \qquad K_1^i(0) = 0 \end{aligned}$$

Assumption 1 is simply that the level of mitigation and investment in adaptation cannot be negative. When $m^i = 0$, a country generates its baseline emissions, i.e. the quantity of emissions that would occur in a world without any consideration of damages.

Assumption 2 governs the properties of the benefit function. We assume that benefits increase at a decreasing rate with both adaptation and aggregate mitigation. We specify the benefit function as joint in $m^i + m^{-i}$ and a^i, and not separable, since it is reasonable to assume that a country's level of adaptation will impact the benefit to mitigation, and vice versa. In particular, we assume that the cross-partial is negative, which implies that adaptation reduces the marginal benefit to mitigation, or rather, adaptation reduces the marginal damage of increased emissions.

Notice that Assumption 2 defines strict concavity with respect to adaptation and total mitigation, $m^i + m^{-i}$. However, since $m^i + m^{-i}$ is a linear combination of m^i and m^{-i}, we can derive a concavity result with respect to adaptation and individual mitigation. Assumption 2 implies that B^i is jointly concave (though not strictly) with respect to m^i, m^{-i}, and a^i for all i.[5]

Assumption 3 contains standard strict convexity assumptions for the cost functions. We assume that marginal costs are zero for the first unit of mitigation and adaptation, but increase thereafter.

3.3.1 Nash Equilibrium in the Noncooperative Game

We begin by analyzing the Nash equilibrium of the model without making further assumptions on country-specific parameters or policy restrictions. In this setting, countries maximize their individual payoff without consideration of the effect on the foreign country.

To start, notice that our assumptions guarantee that the nonnegativity constraints will never bind.[6] Therefore, the maximization problem of each country is solved by the following first-order conditions.

$$\frac{\partial \Pi^i}{\partial m^i} = B_1^i(m^i + m^{-i}, a^i) - C_1^i(m^i) = 0 \tag{3.4}$$
$$\frac{\partial \Pi^i}{\partial a^i} = B_2^i(m^i + m^{-i}, a^i) - K_1^i(a^i) = 0 \tag{3.5}$$

Since emissions reduction is a global public good, the benefits of mitigation are shared by all. However, in maximizing equation (3.3), countries only consider the marginal benefit to themselves. Thus, equation (3.4) differs from any planning solution since it lacks account of foreign marginal benefits. However, since adaptation provides a private benefit, the FOC is the same in both the planning and game solutions.[7]

[5] B^i is not strictly concave with respect to m^i, m^{-i}, and a^i because there are a continuum of (m^i, m^{-i}) that produce any given $m^i + m^{-i}$. Thus, for a fixed a^i, B^i will be constant over this continuum.

[6] The marginal benefit of mitigation and adaptation is assumed to be positive for any level of foreign mitigation, while the marginal costs are assumed to be zero for the first units.

[7] We omit a general discussion of the social planner's problem since it is not relevant to our main results. Still, it is straightforward to show that aggregate mitigation is undersupplied and adaptation is oversupplied in the Nash equilibrium relative to the social optimum. The first order conditions that characterize the social optimum with a purely utilitarian objective function are

$$\frac{\partial \Pi^{SO}}{\partial m^i} = B_1^H(m^i + m^{-i}, a^H) + B_1^F(m^i + m^{-i}, a^F) - C_1^i(m^i) = 0$$
$$\frac{\partial \Pi^{SO}}{\partial a^i} = B_2^i(m^i + m^{-i}, a^i) - K_1^i(a^i) = 0$$

Notice that we cannot define explicit best-response functions with respect to foreign adaptation, which plays no direct role in home country decisions. What matters is foreign emissions. Foreign adaptation is still chosen strategically and jointly with foreign mitigation, but the home country responds directly to emissions via changes in marginal benefits. In other words, foreign mitigation, m^{-i}, completely determines the optimal mitigation and adaptation decisions of country i.

In our analysis, we assume that equations (3.4) and (3.5) can be solved for values (m^{i*}, a^{i*}) that maximize equation (3.3) for any $m^{-i} \geq 0$.[8] Since we are maximizing a strictly concave objective function over a convex constraint set, (m^{i*}, a^{i*}) will be a unique global maximum with respect to m^{-i}.

Proposition 1 *The best-response functions $m^{i*}(m^{-i})$ and $a^{i*}(m^{-i})$ are continuous, downward sloping, and greater than zero for all $m^{-i} \geq 0$.*

Proof: The slopes of the best-response functions can be computed by taking the total differential of the system of FOC's in equations (3.4) and (3.5). Using the Implicit Function Theorem, we can isolate the effects of a marginal change in m^{-i} by computing

$$\begin{bmatrix} \frac{\partial m^{i*}}{\partial m^{-i}} \\ \frac{\partial a^{i*}}{\partial m^{-i}} \end{bmatrix} = - \begin{bmatrix} (B_{11}^i - C_{11}^i) & B_{12}^i \\ B_{12}^i & (B_{22}^i - K_{11}^i) \end{bmatrix}^{-1} \begin{bmatrix} B_{11}^i \\ B_{12}^i \end{bmatrix} \tag{3.6}$$

with partial derivatives evaluated at $(m^{i*}, m^{-i}, a^{i^*})$. The inverse matrix is guaranteed to exist by the second-order condition's for strict concavity in assumption 2. The determinant of the matrix being inverted is

$$D = \left(B_{11}^i - C_{11}^i\right)\left(B_{22}^i - K_{11}^i\right) - \left(B_{12}^i\right)^2 > 0 \tag{3.7}$$

using assumption 2. Thus the matrix is nonsingular and invertible.

The slopes of the best-response curves are

$$\frac{\partial m^{i*}}{\partial m^{-i}} = -\frac{1}{D}\left[\left(B_{22}^i - K_{11}^i\right)B_{11}^i - \left(B_{12}^i\right)^2\right] < 0 \quad \forall\, m^{-i} \geq 0 \tag{3.8}$$

$$\frac{\partial a^{i*}}{\partial m^{-i}} = \frac{B_{12}^i C_{11}^i}{D} < 0 \quad \forall\, m^{-i} \geq 0 \tag{3.9}$$

The signs follow from Assumptions 2 and 3, which also guarantee that all partial derivatives in the above expressions are defined and continuous over all possible values of m^i,

[8] Essentially, we assume that given any a^i, $B_1^i < C_1^i$ for a sufficiently large m^i, and similarly, given any $(m^i + m^{-i})$, $B_2^i < K_1^i$ for a sufficiently large a^i.

m^{-i}, and a^i. Furthermore, since we always have $D > 0$, the slopes of the best-response functions are defined for all $m^{-i} \geq 0$. Thus, the best-response functions are continuous with respect to m^{-i}. ■

The freeriding incentive is clear from proposition 1. If the foreign country increases its mitigative effort, other things equal, the home country reduces both mitigation and adaptation. In other words, let your opponent do the work and reduce your own expenditures. Similarly, the home country will increase both mitigative and adaptive efforts when the foreign country reduces its mitigation.[9]

To identify a Nash equilibrium, we need to find a point (m^H_{NE}, m^F_{NE}) such that chosen mitigation rates are a best-response to each other. There is no similar condition for adaptation. Obviously adaptation will influence the optimal response of m^i to m^{-i}, and in that sense, adaptation has an effect on strategic interaction. Still, as discussed above, countries do not respond directly to foreign levels of adaptation. Given our assumptions, the model has a unique Nash equilibrium, as shown in Proposition 2.

Proposition 2 *A Nash equilibrium of the noncooperative game exists and is unique.*

Proof: Since the mitigation best-response curves, $m^{i*}(m^{-i})$, are downward sloping, continuous, and positive for all $m^{-i} \geq 0$, they must intersect at least once. This intersection, represents a Nash equilibrium in both mitigation and adaptation (since optimal adaptation varies as m^{-i} changes as well). We now show that this intersection is unique.

A sufficient condition for the mitigation best-response curves to intersect only once is that for any fixed $m^F > 0$,[10]

$$\frac{\partial m^{F*}}{\partial m^H}\left(m^{H*}(m^F), m^{F*}, a^{F*}\right) > \frac{1}{\frac{\partial m^{H*}}{\partial m^F}\left(m^{H*}, m^F, a^{H*}\right)} \tag{3.10}$$

Essentially, when drawn with m^F on the vertical axis and m^H on the horizontal axis, this requires that the slope of the best-response curve for m^F appear "flatter" for any value of m^H.

Equation (3.8) in the proof of Proposition 1 gives the slope of the mitigation best-response curve. Substituting for the inverse value of the determinant, D, this can be shown

[9] The main result in Ebert and Welsch (2011) is that situations exist where mitigation best-response curves can be upward sloping. This drives further results in Ebert and Welsch (2012) and Eisenack and Kähler (2016). In our model, the assumption of strict concavity of the benefit function, and in particular, the Hessian condition of Assumption 2 preclude this result.

[10] Note that m^F is fixed, whereas m^{H*} and m^{F*} represent optimal responses, meaning that m^F and m^{F*} will generally represent two distinct levels of F's mitigation (except at the Nash equilibrium) in equation (3.10).

to be

$$\frac{\partial m^{i*}}{\partial m^{-i}} = -\frac{\left(B_{22}^{i} - K_{11}^{i}\right) B_{11}^{i} - \left(B_{12}^{i}\right)^{2}}{\left(B_{11}^{i} - C_{11}^{i}\right)\left(B_{22}^{i} - K_{11}^{i}\right) - \left(B_{12}^{i}\right)^{2}} \quad \in (-1, 0) \quad \forall\, m^{-i} \geq 0 \tag{3.11}$$

from Assumptions 2 and 3. But then for any m^F, it must be that

$$\frac{\partial m^{F*}}{\partial m^{H}}\left(m^{H*}(m^F), m^{F*}, a^{F*}\right) > -1 > \frac{1}{\frac{\partial m^{H*}}{\partial m^{F}}\left(m^{H*}, m^{F}, a^{H*}\right)} \tag{3.12}$$

Thus, the best-response curves are guaranteed to intersect once and only once. ■

Figure 3.1 presents an arbitrary depiction of the best-response curves and the Nash equilibrium. It is important to note that in Figure 3.1a, the best-response mitigation levels, m^{i*}, implicitly account for optimal adaptation given m^{-i}. This is consistent with the results of Propositions 1 and 2. In other words, adaptation varies along these curves. Similarly, optimal mitigation for country i varies along i's adaptation best-response curve, $a^{i*}(m^{i*}, m^{-i})$.

3.4 The Strategic Effects of Adaptation

The simple example in Section 3.2 shows how countries can be made better off when adaptation is constrained or when it becomes less beneficial at the margin. This leads us to ask what conditions must be satisfied for this to hold more generally? We begin by examining this question in the context of the best response curves derived in Section 3.3.1. Although we are focusing on the constrained adaptation scenario, the graphical analysis is qualitatively the same for considering decreases in the marginal benefit of adaptation.

In Figure 3.2, the dashed lines represent an arbitrary example of mitigation best-response curves in the unconstrained world, where countries can adapt freely. From our assumptions and the first-order conditions in Equations (3.4)-(3.5), we know that adaptation will be positive given any level of foreign mitigation, m^{-i}.

Now consider what happens when country F is restricted from adapting. We assume that when adaptation is constrained to zero, countries effectively maximize the payoff function from the Hoel (1991) model in equation (3.2).[11] As a result of this constraint, the marginal damage (benefit) of emissions (mitigation) for country F rises over all levels of m^H. Thus, optimal mitigation in F also increases given any m^H, implying an upward shift

[11] Many of our results in Section 3.3.1 carry over to the game with only mitigation. In particular, it can be shown that the best-response curves are continuous and downward sloping with slope greater than -1, and that the Nash equilibrium is unique. Proofs of these results are analogous to the those in Section 3.3.1 and are omitted.

of the best-response curve of country F. In addition, the slope of the new best-response curve will be steeper. Intuitively, as m^H decreases, country F must respond without the use of adaptation, whereas before, it could respond with both increased mitigation and adaptation. Thus, additional mitigation will substitute for the adaptation that would have otherwise increased, creating a steeper best-response curve.[12]

The new Nash equilibrium is represented by point B in Figure 3.2. Anticipating increased mitigation from country F, country H finds it optimal to decrease its own. This results in a Nash equilibrium with higher m^F and lower m^H. Since country F is now optimizing with respect to one less argument and m^H_{NE} is lower, F must be worse off. However, country H is better off since total external emissions have decreased, and it is still able to adapt. Country F has provided additional benefits of mitigation and inadvertently aided country H, which now finds it optimal to reduce its own mitigation (and adaptation), thereby lowering costs as well.

When country H is also restricted from adapting, the Nash equilibrium shifts to point C in Figure 3.2. Relative to point B, mitigation in country H must increase and mitigation in country F must decrease. As drawn, both m^H and m^F are higher at point C than point A. As we will show later, this need not be the case for both countries. A Nash equilibrium where the constraint results in decreased mitigation for one country is possible, as can be verified by imagining different rightward shifts of the dashed best-response curves. However, it must be the case that aggregate emissions are lower at points B and C than point A. This follows from the observation that the slope of any mitigation best-response curve must be greater than -1.

In terms of payoffs, when we move from point B to point C, country H is worse off since it has lost the ability to optimize over adaptation, and it elicits lower mitigation from country F. Country F, however, is better off since H now mitigates more. Country F can relax its mitigation expenditures and allow H to contribute more of the work.

From this analysis, it's clear that restricting only one country will increase the payoff of its rival at its own expense. This holds whether the other country is already constrained or not. However, the more interesting question is how payoffs change between points A and C, i.e. when we move from a situation in which everyone can adapt to one where no one adapts. Notice that there are two opposing effects in this transition. On one hand, the inability to adapt leads to lower payoffs at home since countries must increase expenditures on mitigation (for any level of m^{-i}) and can no longer optimize over two arguments. This is the move from point A to point B. However, the foreign country also loses the ability to adapt, and this results in greater foreign mitigation given any level of home mitigation,

[12]We omit the mathematical proofs of these results.

which increases payoffs at home. This is the move from B to C. It's not clear without more information which effect is stronger.

When will the benefit from the reduction in global emissions offset the payoff loss from not being able to fully adapt? At first glance, calculus seems of little use since we are comparing discrete jumps in the action space. However, we can transform the question. In the context of a constraint on adaptation, we can consider marginal changes in the constraint, beginning with a constraint set exactly at the unconstrained Nash equilibrium levels of adaptation. For shocks to the marginal benefit of adaptation, we can also consider marginal changes rather than discrete jumps.

3.4.1 Constrained Adaptation

Suppose that we are in a world with constraints on adaptation, and these constraints are binding for both countries in the Nash equilibrium. Now consider marginally tightening the constraints. If this results in positive marginal payoff gains over some interval, then we can say that over that interval, countries are made better off by restricting adaptation. If this property holds over the entire region of effective adaptation constraints, $[0, a^i_{NE}]$, then countries will be better off in a world without adaptation.

This thought experiment follows Gaudet and Salant (1991), who consider subsets of firms in oligopoly models and the conditions under which payoffs to these subsets will increase when their strategic variables are marginally reduced (e.g. output in a Cournot model). A key difference is that our agents have multiple weapons, and we consider constraints on the private choice variable (adaptation), not the strategic substitute (mitigation).

The Lagrangian that represents country i's maximization problem subject to a constraint on adaptation is

$$\mathcal{L}^i = B^i(m^i + m^{-i}, a^i) - C^i(m^i) - K^i(a^i) + \lambda^i(\bar{a}^i - a^i) \tag{3.13}$$

where $\bar{a}^i$ is the level of the adaptation constraint for country i. The resulting Kuhn-Tucker conditions are

$$B^i_1(m^i + m^{-i}, a^i) - C^i_1(m^i) = 0 \tag{3.14}$$

$$B^i_2(m^i + m^{-i}, a^i) - K^i_1(a^i) - \lambda^i = 0 \tag{3.15}$$

$$\lambda^i(\bar{a}^i - a^i) = 0 \tag{3.16}$$

for all i. It is straightforward to extend the results of Section 3.3.1 and show that Nash equilibrium mitigation is positive and unique given any level of a binding constraint.

When we analyze the effects of a tighter constraint, we will be most interested in how Nash equilibrium mitigation, m^i_{NE}, changes. It is conceivable that for appropriately configured reductions in the constraints, one country could substitute a large amount of mitigation for the lost adaptation, causing the opposing country to greatly reduce adaptation in the new Nash equilibrium, so much so that its constraint no longer binds. We are focusing on situations where both constraints are marginally tightened in ways such that both continue to bind. Consider the following explanation.

One way to view a binding constraint is that given m^{-i}, you want to adapt more than you can. As m^{-i} increases, your marginal benefits decrease, and you want to adapt and mitigate less. Thus, given any binding $\bar{a}^i > 0$, there exists some $\bar{m}^{-i} > m^{-i}$ such that you would no longer be constrained. In other words, for m^{-i} sufficiently high, optimal adaptation is less than the level of the constraint. But this means that if $m^{-i} < \bar{m}^{-i}$, a marginal reduction in $\bar{a}^{-i}$ will only increase m^{-i} by a small amount. For a small enough change, i will remain constrained. This holds for any $\bar{a}^i$ less than the unconstrained adaptation level.

On the other hand, if we are beginning with a constraint set exactly at the optimal level of adaptation given m^{-i}, the increased foreign mitigation that results from a tighter foreign constraint will cause home adaptation to fall below its own constraint. However, if we simultaneously command a tighter home constraint, we can simply specify the constraint to be slightly less than the new optimal level of adaptation. In a similar manner as discussed above, we can identify changes in both constraints that continue to bind.

The reason this property is useful is that it allows us to ignore equations (3.15) and (3.16) since the changes in adaptation levels will be equal to the changes in the constraints. However, we have two countries, and therefore, two equation (3.14)'s. In assessing how country H's mitigation changes, we must take account of how country F's mitigation changes as well.

We can estimate the mitigation changes with a linear approximation and application of the Implicit Function Theorem. Differentiation of the two FOC's for mitigation leads to the following system of linear approximations.

$$\begin{bmatrix} dm^H_{NE} \\ dm^F_{NE} \end{bmatrix} = \begin{bmatrix} \left(B^H_{11} - C^H_{11}\right) & B^H_{11} \\ B^F_{11} & \left(B^F_{11} - C^F_{11}\right) \end{bmatrix}^{-1} \begin{bmatrix} -B^H_{12} & 0 \\ 0 & -B^F_{12} \end{bmatrix} \begin{bmatrix} d\bar{a}^H \\ d\bar{a}^F \end{bmatrix} \tag{3.17}$$

$$= \frac{1}{F} \begin{bmatrix} -\left(B^F_{11} - C^F_{11}\right) B^H_{12} & B^H_{11} B^F_{12} \\ B^F_{11} B^H_{12} & -\left(B^H_{11} - C^H_{11}\right) B^F_{12} \end{bmatrix} \begin{bmatrix} d\bar{a}^H \\ d\bar{a}^F \end{bmatrix} \tag{3.18}$$

$$= \begin{bmatrix} \frac{\partial m^H_{NE}}{\partial \bar{a}^H} & \frac{\partial m^H_{NE}}{\partial \bar{a}^F} \\ \frac{\partial m^F_{NE}}{\partial \bar{a}^H} & \frac{\partial m^F_{NE}}{\partial \bar{a}^F} \end{bmatrix} \begin{bmatrix} d\bar{a}^H \\ d\bar{a}^F \end{bmatrix} \tag{3.19}$$

where F is the determinant of the matrix being inverted, such that

$$F = -B_{11}^F C_{11}^H - B_{11}^H C_{11}^F + C_{11}^H C_{11}^F > 0 \tag{3.20}$$

by the concavity assumptions. Thus, the inverted matrix in equation (3.17) is nonsingular and invertible. Also, note that the functions in equations (3.17)-(3.20) are evaluated at Nash equilibrium mitigation levels and constrained adaptation levels, $(m_{NE}^H, \bar{a}^H)$ and $(m_{NE}^F, \bar{a}^F)$, as described by the Kuhn-Tucker conditions. We will continue suppressing the arguments for the remainder of the paper to minimize notation.

The partial derivatives in equations (3.18) and (3.19) can be signed using the concavity assumptions. We find that $\frac{\partial m_{NE}^i}{\partial \bar{a}^i} < 0$ and $\frac{\partial m_{NE}^i}{\partial \bar{a}^{-i}} > 0$. That is, a marginal relaxation in a country's own adaptation constraint lowers its mitigation, while relaxing the foreign constraint increases home mitigation in the Nash equilibrium.[13] This is not surprising since adaptation and mitigation are substitutes domestically, and countries trade-off mitigation internationally. Our assumptions also guarantee that the slope of the equilibrium response function $\frac{\partial m_{NE}^i}{\partial \bar{a}^j}$ is continuous in $\bar{a}^j$. Since Nash equilibrium mitigation is positive and unique given any level of the constraint, the equilibrium response function will be continuous in $\bar{a}^j$ as well.

When we consider the effects of simultaneous changes in both countries constraints, we cannot sign the total effect without further assumptions. This is because the effects of home and foreign adaptation on mitigation work in opposite directions. While it is possible to have a reduction in both constraints lead to decreased mitigation in one country, it is not possible for both countries to decrease mitigation, as discussed previously with respect to Figure 3.2. We can see this mathematically as well. From equation (3.18), if the magnitudes of negative change in both constraints are identical, a necessary condition for mitigation to decrease in country F is that $B_{11}^F B_{12}^H > B_{11}^H B_{12}^F$. However, this condition also implies that m_{NE}^H must increase from the top row of equation (3.18).

The effects on mitigation are interesting, but we also care about the payoff effects. At Nash equilibrium levels of m^i, differentiation of equation (3.3) with respect to changes in the adaptation constraints gives

$$\begin{aligned} d\Pi_{NE}^i = &\left[\frac{\partial \Pi^i}{\partial m^i}\frac{\partial m_{NE}^i}{\partial \bar{a}^i} + \frac{\partial \Pi^i}{\partial m^{-i}}\frac{\partial m_{NE}^{-i}}{\partial \bar{a}^i} + \frac{\partial \Pi^i}{\partial a^i}\frac{\partial a_{NE}^i}{\partial \bar{a}^i}\right] d\bar{a}^i \\ &+ \left[\frac{\partial \Pi^i}{\partial m^i}\frac{\partial m_{NE}^i}{\partial \bar{a}^{-i}} + \frac{\partial \Pi^i}{\partial m^{-i}}\frac{\partial m_{NE}^{-i}}{\partial \bar{a}^{-i}} + \frac{\partial \Pi^i}{\partial a^i}\frac{\partial a_{NE}^i}{\partial \bar{a}^{-i}}\right] d\bar{a}^{-i} \end{aligned} \tag{3.21}$$

[13] A relaxation in the constraint will only result in changes to mitigation levels when the constraints are set below the unconstrained levels.

where functions are again evaluated at Nash equilibrium mitigation and constrained levels of adaptation as described by the Kuhn-Tucker conditions. However, countries are fully maximizing with respect to mitigation, and thus, the envelope theorem tells us that $\frac{\partial \Pi^i}{\partial m^i} = 0$. Furthermore, the change in a country's adaptation level is equal to the change in the constraint, as previously discussed.

$$\Rightarrow d\Pi^i_{NE} = \frac{\partial \Pi^i}{\partial m^{-i}} \left[\frac{\partial m^{-i}_{NE}}{\partial \bar{a}^i} d\bar{a}^i + \frac{\partial m^{-i}_{NE}}{\partial \bar{a}^{-i}} d\bar{a}^{-i} \right] + \frac{\partial \Pi^i}{\partial a^i} d\bar{a}^i \tag{3.22}$$

Notice that $\frac{\partial \Pi^i}{\partial a^i} = \lambda^i > 0$ from the Kuhn-Tucker conditions in equations (3.14)-(3.16), and represents the payoff gain from a marginal relaxation of the constraint. We also know that $\frac{\partial m^i_{NE}}{\partial \bar{a}^i} < 0$ and $\frac{\partial m^i_{NE}}{\partial \bar{a}^{-i}} > 0$ from our earlier discussion. Thus, for a marginally tighter constraint ($d\bar{a}^i < 0$ for all *i*), the first element inside the brackets in equation (3.22) is negative and the second element is positive.

The tradeoff is clear; further constraining adaptation in one of the countries directly reduces its payoff since it pushes the country further away from its desired mix of adaptation and mitigation, while also leading to reduced foreign mitigation in the new Nash equilibrium. On the other hand, a tighter foreign constraint elicits greater foreign mitigation, which increases the payoff at home. If, however, the net effect on foreign mitigation is negative, then the entire expression in equation (3.22) is also negative, and payoffs decrease. It is obvious that for payoffs to increase, there must be a net-increase in foreign mitigation that outweighs the payoff loss from not being able to fully adapt. However, as Proposition 3 shows, as long as foreign mitigation increases, home payoffs are guaranteed to increase as adaptation is restricted in the neighborhood of the unconstrained Nash equilibrium.

Proposition 3 *Consider marginally constraining adaptation in both countries below the unconstrained Nash equilibrium levels. If foreign mitigation increases, then home payoffs will also increase.*

Proof: Beginning in the unconstrained Nash equilibrium with constraints set exactly at the Nash equilibrium levels of adaptation, countries are effectively unconstrained and $\frac{\partial \Pi^i}{\partial a^i} = 0$. Thus, by the envelope theorem, the effect of marginally tightened constraints from the Nash equilibrium levels is

$$d\Pi^i = \frac{\partial \Pi^i}{\partial m^{-i}} \left[\frac{\partial m^{-i}_{NE}}{\partial \bar{a}^i} d\bar{a}^i + \frac{\partial m^{-i}_{NE}}{\partial \bar{a}^{-i}} d\bar{a}^{-i} \right] = B^i_1 \left[\frac{\partial m^{-i}_{NE}}{\partial \bar{a}^i} d\bar{a}^i + \frac{\partial m^{-i}_{NE}}{\partial \bar{a}^{-i}} d\bar{a}^{-i} \right] \tag{3.23}$$

The change in payoff is completely determined by the change in foreign mitigation. If foreign mitigation increases (decreases), then home country payoffs will rise (fall). ■

Proposition 3 further implies that if foreign mitigation increases, there will exist an interval of adaptation constraints in the home country, $[\bar{a}^i_L, a^i_{NE})$, with simultaneous reductions in the foreign country, over which home payoffs rise. Of course, the exact lower bound of this interval will depend on the rates at which the two adaptation constraints are tightened in relation to each other. Since a country is unambiguously better off as foreign adaptation is constrained, the foreign rate of change matters. And heterogenous countries will have different unconstrained Nash equilibrium levels of adaptation.

However, in general terms, our result does not rely on how the constraints are changed in relation to one another. We do not assume that changes are symmetric in nominal or percentage terms; they may be completely heterogenous. The result holds that if we consider marginally tightened constraints in both countries and foreign mitigation increases, then home payoffs will increase over some interval. Consequently, if there were a ceiling set on adaptation for each country in its own interval, then raising the ceilings would induce both countries to substitute adaptation for abatement, shifting the Nash equilibrium in the direction of the unconstrained outcome and resulting in both countries being worse off.

Without further assumptions, we cannot say whether these intervals contain zero adaptation. To some extent, it is unimportant. The point is that there will be too much adaptation in the unconstrained Nash equilibrium, in the sense that limiting countries from adapting will make everyone better off. This result holds whenever both countries increase mitigation as adaptation is constrained.

In Section 3.2, we presented a simple example with symmetric countries and compared the unconstrained Nash equilibrium ($a_{NE} = 5$) to the Nash equilibrium without adaptation. If we instead consider symmetric marginal changes in the constraint, we can easily show that $m_{NE}(\bar{a}) = 46 - \frac{\bar{a}}{5}$, $\Pi_{NE}(\bar{a}) = 23276 - \frac{12}{5}\bar{a} - \frac{39}{25}\bar{a}^2$, and $\frac{\partial \Pi_{NE}}{\partial \bar{a}}(\bar{a}) = -\frac{12}{5} - \frac{78}{25}\bar{a}$, which confirms that Nash equilibrium payoffs and mitigation both increase as the adaptation constraints are lowered over the entire interval $[0, 5]$. Figure 3.3 shows this result graphically.

Suppose instead that the payoff function were given by

$$\Pi^i = 2\left[200 - (m^i + m^{-i})\right](m^i + m^{-i}) + (100 - a^i)a^i - (m^i + m^{-i})a^i - (m^i)^2 - (a^i)^2 \quad (3.24)$$

This can also be easily solved by hand to show that countries are better off in the Nash equilibrium without adaptation. However, in this case, the payoff increasing interval of constraints does not include zero. As shown in Figure 3.4, maximum Nash equilibrium payoffs are actually achieved when the adaptation constraint is tightened approximately 61% below the unconstrained level. If the constraint is lowered further, the loss from not being able to adapt begins to outweigh the gain from increased foreign mitigation.

While we have concentrated this section on the idea of constraints to adaptation, we can derive analogous results with a tax on adaptation that is refunded lump-sum, provided that countries do not consider the size of the refund in their optimization problem. In other words, for any constraint, we can identify a refunded tax on adaptation that replicates Nash equilibrium mitigation, adaptation, and payoffs under the constraint. It is also possible for a non-refunded tax on adaptation to improve payoffs in Nash equilibrium. Such a tax is analyzed in the same way as a shock to the marginal benefit of adaptation in Section 3.4.2, where a negative shock can be interpreted as an increase in the non-refunded adaptation tax.

3.4.2 Shocks to the Marginal Benefit of Adaptation

In a classic paper, Bulow et al. (1985) consider a producer who is a monopolist in one market and a duopolist in another. They show that it's possible to have situations where the monopolist receives a positive shock to its marginal revenue in the monopoly market, and the monopolist is worse off in the resulting Nash equilibrium due to strategic effects in the duopoly market.

The analogy to our model is to think of adaptation in each country as the monopolist good, and mitigation as the duopolist good. We find that we can generate a similar result when we consider a shock to the marginal benefit of the monopolist good, even when that shock occurs for both countries. Such a shock might be thought of as a technological advancement (e.g., a new climate-resistent seed), or conversely, a technology that did not perform as well as expected (e.g., a climate-resistent seed that does not perform as expected).

Following Bulow et al. (1985), we model this by adding the term $Z^i a^i$ to the payoff function in equation (3.3), such that

$$\Pi^i(m^i, a^i) = B^i(m^H + m^F, a^i) - C^i(m^i) - K^i(a^i) + Z^i a^i \tag{3.25}$$

with modified first-order conditions

$$\frac{\partial \Pi^i}{\partial m^i} = B_1^i(m^i + m^{-i}, a^i) - C_1^i(m^i) = 0 \tag{3.26}$$

$$\frac{\partial \Pi^i}{\partial a^i} = B_2^i(m^i + m^{-i}, a^i) + Z^i - K_1^i(a^i) = 0 \tag{3.27}$$

A change in Z^i represents a shock to marginal benefits, where a +1-unit change shifts the marginal benefit curve upward by 1-unit, holding mitigation constant. To identify the effects of changes in Z^i on Nash equilibrium mitigation and adaptation, we totally differentiate equations (3.26) and (3.27) and solve the following system of equations.

$$\begin{bmatrix} B_{11}^H - C_{11}^H & B_{12}^H & B_{11}^H & 0 \\ B_{12}^H & B_{22}^H - K_{11}^H & B_{12}^H & 0 \\ B_{11}^F & 0 & B_{11}^F - C_{11}^F & B_{12}^F \\ B_{12}^F & 0 & B_{12}^F & B_{22}^F - K_{11}^F \end{bmatrix} \begin{bmatrix} dm_{NE}^H \\ da_{NE}^H \\ dm_{NE}^F \\ da_{NE}^F \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ -1 & 0 \\ 0 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} dZ^H \\ dZ^F \end{bmatrix} \tag{3.28}$$

$$\Rightarrow \begin{bmatrix} dm_{NE}^H \\ da_{NE}^H \\ dm_{NE}^F \\ da_{NE}^F \end{bmatrix} = \frac{1}{G} \cdot$$
$$\begin{bmatrix} B_{12}^H\left[(B_{11}^F - C_{11}^F)(B_{22}^F - K_{11}^F) - (B_{12}^F)^2\right] & B_{12}^F\left[(B_{12}^H)^2 - B_{11}^H(B_{22}^H - K_{11}^H)\right] \\ -(B_{12}^F)^2 C_{11}^H - (B_{22}^F - K_{11}^F)[C_{11}^H C_{11}^F - B_{11}^H C_{11}^F - B_{11}^F C_{11}^H] & B_{12}^F B_{12}^H C_{11}^H \\ B_{12}^H\left[(B_{12}^F)^2 - B_{11}^F(B_{22}^F - K_{11}^F)\right] & B_{12}^F\left[(B_{11}^H - C_{11}^H)(B_{22}^H - K_{11}^H) - (B_{12}^H)^2\right] \\ B_{12}^H B_{12}^F C_{11}^F & -(B_{12}^H)^2 C_{11}^F - (B_{22}^H - K_{11}^H)[C_{11}^H C_{11}^F - B_{11}^H C_{11}^F - B_{11}^F C_{11}^H] \end{bmatrix}$$
$$\cdot \begin{bmatrix} dZ^H \\ dZ^F \end{bmatrix} \tag{3.29}$$

where G is defined as the determinant of the matrix that is inverted. Using Assumptions 1-3, G can be shown to be positive, implying that the matrix is nonsingular.

$$\begin{aligned} G = & C_{11}^F(B_{22}^F - K_{11}^F)\left[(B_{12}^H)^2 - B_{22}^H B_{11}^H + K_{11}^H B_{11}^H\right] \\ & + C_{11}^H(B_{22}^H - K_{11}^H)\left[(B_{12}^F)^2 - B_{22}^F B_{11}^F + K_{11}^F B_{11}^F\right] \\ & + (B_{22}^H - K_{11}^H)(B_{22}^F - K_{11}^F) C_{11}^H C_{11}^F > 0 \end{aligned} \tag{3.30}$$

The expressions in equation (3.29) can be signed using Assumptions 1-3 to show that $\frac{\partial m_{NE}^i}{\partial Z^i} < 0$, $\frac{\partial a_{NE}^i}{\partial Z^i} > 0$, $\frac{\partial m_{NE}^i}{\partial Z^{-i}} > 0$, and $\frac{\partial a_{NE}^i}{\partial Z^{-i}} > 0$. In the Nash equilibrium, a country decreases mitigation in response to a positive shock to its own marginal benefit of adaptation, and similarly increases mitigation when its opponent experiences the shock. Meanwhile, Nash equilibrium adaptation increases for both countries – a country that receives a positive shock finds adaptation more beneficial and thereby decreases mitigation, which causes the opposing country to increase both mitigation and adaptation.

Thus, a country that receives a positive shock enjoys the direct benefit from the shock as well as the indirect benefit of increased foreign mitigation. On the other hand, payoffs for the foreign country decrease due to lower mitigation from the shock-receiving country.

In the context of Figure 3.2, point A could refer to a situation with $Z^i = 0$ for all i. If F experiences a negative shock to the marginal benefit of adaptation, say $Z^F = -5$, it becomes optimal to reduce adaptation for any m^H, thereby raising the marginal benefit of mitigation, and causing the mitigation best-response curve to shift up. The Nash equilibrium moves to point B, where F is worse off, and H is better off. If H experiences the negative shock as well, similar reasoning shifts the Nash equilibrium to point C. Relative to point B, F is now better off and H is worse off. However, in order to use calculus to analyze the payoff change from point A to point C, we will again modify the problem and consider marginal changes in Z.

Total differentiation of equation (3.25) with respect to its own shock variable, Z^i, as well as the foreign shock variable, Z^{-i}, gives

$$d\Pi^i_{NE} = \left[\frac{\partial \Pi^i}{\partial m^i}\frac{\partial m^i_{NE}}{\partial Z^i} + \frac{\partial \Pi^i}{\partial m^{-i}}\frac{\partial m^{-i}_{NE}}{\partial Z^i} + \frac{\partial \Pi^i}{\partial a^i}\frac{\partial a^i_{NE}}{\partial Z^i} + a^i_{NE}\right] dZ^i + \left[\frac{\partial \Pi^i}{\partial m^i}\frac{\partial m^i_{NE}}{\partial Z^{-i}} + \frac{\partial \Pi^i}{\partial m^{-i}}\frac{\partial m^{-i}_{NE}}{\partial Z^{-i}} + \frac{\partial \Pi^i}{\partial a^i}\frac{\partial a^i_{NE}}{\partial Z^{-i}}\right] dZ^{-i} \tag{3.31}$$

Since we are calculating the changes in payoffs relative to the initial Nash equilibrium, regardless of the pre-existing level of Z^i and Z^{-i}, it must be that $\frac{\partial \Pi^i}{\partial m^i} = \frac{\partial \Pi^i}{\partial a^i} = 0$ for small changes. Therefore, equation (3.31) simplifies to

$$d\Pi^i = \frac{\partial \Pi^i}{\partial m^{-i}}\left[\frac{\partial m^{-i}_{NE}}{\partial Z^i} dZ^i + \frac{\partial m^{-i}_{NE}}{\partial Z^{-i}} dZ^{-i}\right] + a^i_{NE} dZ^i \tag{3.32}$$

There are two important terms in equation (3.32): a direct effect from the change in marginal benefits and an indirect effect that depends on how foreign mitigation changes in response to the shock. The first term on the right (the indirect effect) will be positive if foreign mitigation increases, while the second term on the right (the direct effect) will inherit the same sign as the change in Z^i.

For a negative shock, it can be shown that Nash equilibrium mitigation must increase for at least one country.[14] However, in the symmetric country case, mitigation will increase for both. Thus, if adaptation in the initial Nash equilibrium is sufficiently low, then a universal negative shock can increase payoffs for all countries.

Alternatively, a positive shock in the symmetric case can reduce everyone's payoffs if the reduction in foreign mitigation outweighs the payoff gain from increased adaptation benefits. However, $\frac{\partial a^i_{NE}}{\partial Z} > 0$, and if we were to imagine setting Z at higher and higher levels (and considering small changes from those levels), adaptation would continually increase and mitigation would decrease. This implies that $\frac{\partial \Pi^i}{\partial m^{-i}} = \frac{\partial B^i}{\partial m^{-i}} = \frac{\partial B^i}{\partial m^i} = \frac{\partial C^i}{\partial m^i}$ must be decreasing as well since mitigation is set optimally. We should therefore see the change in payoffs turn positive at some level of $Z = \bar{Z}$, since the first term of equation

[14] Again, imagine different rightward shifts of the mitigation best-response curves in Figure 3.2.

(3.32) gets closer to zero, while the second term gets more positive. For $Z > \bar{Z}$, the payoff change remains positive. So, while it is possible that positive shocks will reduce Nash equilibrium payoffs when adaptation is low, large enough shocks will have a beneficial effect.

Consider again the simple example presented in Section 3.2. The payoff function that incorporates the Z variable to account for shocks to the marginal benefit of adaptation is given by

$$\Pi^i = 2\left[230 - (m^i + m^{-i})\right](m^i + m^{-i}) + (200 - a^i)a^i - 2(m^i + m^{-i})a^i - (m^i)^2 - (a^i)^2 + Z^i a^i \quad (3.33)$$

In the symmetric country case with identical shocks for both countries, the Nash equilibrium is solved easily.

$$m^i_{NE} = 45 - \frac{Z}{16} \quad (3.34)$$

$$a^i_{NE} = 5 + \frac{5}{16}Z \quad (3.35)$$

Figure 3.5 plots Nash equilibrium payoffs, mitigation, and adaptation for a range of potential Z. For negative shocks, payoffs increase down to $Z = -16$, at which point $a^i_{NE} = 0$. At lower values of Z, optimal adaptation remains at zero, and there are no further payoff gains. For small positive shocks, payoffs decrease. However, using equations (3.32), (3.34), and (3.35), it can be shown that the marginal payoff gain turns positive for $Z > \frac{80}{41} \approx 1.95$, as shown in Figure 3.5a.

3.4.3 Heterogeneous Countries with Opposite Mitigation Effects

Whether we are considering a constraint or a negative productivity shock, payoff gains require an increase in foreign mitigation. With symmetric countries, this condition will always be satisfied, but it will not always hold with heterogeneous countries. Consider a situation in which one country is very effective at adapting relative to another country. Furthermore, suppose that the country with low adaptive capacity is also more sensitive to climate change. That is, the marginal damage of emissions increases at a quicker rate for this country than its opponent. The usual contrast is Bangladesh versus the USA. When adaptation is constrained in such a situation, it is possible that mitigation will only increase for the US, while Bangladesh actually decreases mitigation.

The intuition is that with adaptation, the US is able to offset a much larger fraction of mitigation than Bangladesh. Thus, when adaptation is constrained, the US must heavily substitute with mitigation.[15] Even as the constraint in Bangladesh continues to bind, the relatively large increase in US mitigation could lead to lower Nash equilibrium mitigation in Bangladesh.[16] This can be visualized in Figure 3.2 by imagining that the mitigation best-response curve for Bangladesh only shifts up slightly when it is constrained. We now analyze this more formally for both the constraint and negative shock examples.

In the constraint scenario, equation (3.18) shows that for m^i_{NE} to decrease, we must have

$$-(B^{-i}_{11} - C^{-i}_{11})B^i_{12}d\bar{a}^i < -B^i_{11}B^{-i}_{12}d\bar{a}^{-i} \tag{3.36}$$

Therefore, a necessary condition for equation (3.36) to hold for $d\bar{a}^i, d\bar{a}^{-i} < 0$ is that

$$B^{-i}_{11}B^i_{12}\frac{d\bar{a}^i}{d\bar{a}^{-i}} < B^i_{11}B^{-i}_{12} \tag{3.37}$$

which is satisfied if, for example,

$$B^i_{11} < B^{-i}_{11} \tag{3.38}$$
$$B^{-i}_{12} < B^i_{12} \tag{3.39}$$
$$\text{and } d\bar{a}^i \leq d\bar{a}^{-i} \tag{3.40}$$

Similarly, in the shock scenario, manipulation of the top row of equation (3.29) shows that for m^i_{NE} to decrease after a small negative shock in each country, it must be that

$$B^i_{12}\left[(B^{-i}_{12})^2 - (B^{-i}_{11} - C^{-i}_{11})(B^{-i}_{22} - K^{-i}_{11})\right]\tfrac{dZ^i}{dZ^{-i}} < B^{-i}_{12}\left[(B^i_{12})^2 - B^i_{11}(B^i_{22} - K^i_{11})\right] \tag{3.41}$$

Notice that when $dZ^i = dZ^{-i} < 0$, this condition will hold if both

$$B^{-i}_{12} < B^i_{12} \tag{3.42}$$
$$\text{and } (B^i_{12})^2 - B^i_{11}(B^i_{22} - K^i_{11}) < (B^{-i}_{12})^2 - (B^{-i}_{11} - C^{-i}_{11})(B^{-i}_{22} - K^{-i}_{11}) \tag{3.43}$$

If equation (3.42) is satisfied, then equation (3.43) will also hold when B^i_{11} and B^i_{22} are sufficiently more negative than their foreign counterparts.

In both scenarios, $B^{-i}_{12} < B^i_{12}$ implies that adaptation in $-i$ reduces the marginal ben-

[15] As an example, consider a situation in which the large agricultural sector in the U.S. were prevented from using climate-resistant crops.

[16] Regarding the binding constraint, the reasoning is essentially the same as in Section 3.4.1. A binding constraint indicates that given m^{-i}, you want to adapt more than you can, implying that there exists some $\bar{m}^{-i} > m^{-i}$ at which point you would no longer be constrained. However, if the difference between $\bar{m}^{-i}$ and m^{-i} is sufficiently large, then given small reductions in $\bar{a}^i$ and $\bar{a}^{-i}$, a large increase in m^{-i} could reduce optimal m^i while still maintaining a binding $\bar{a}^i$.

efit of mitigation by more than in i. This is equivalent to saying that adaptation in $-i$ reduces the marginal damage of emissions by more than in i, or in other words, adaptation is relatively more effective for country $-i$. On the other hand, $B^i_{11} < B^{-i}_{11}$ implies that the marginal benefit of mitigation is decreasing faster for i than $-i$, i.e. the marginal damage of emissions is rising faster in i, or rather, i is more sensitive to climate change. Similarly, if $B^i_{22} < B^{-i}_{22}$, then the marginal benefit of adaptation also decreases faster for i.

In summary, we may see Nash equilibrium mitigation decrease for country i if it is more sensitive to climate change and less able to offset damage with adaptation. This is exactly our thought experiment above with Bangladesh. From equation (3.23), in such a situation we know that there exist intervals, $[\bar{a}^i_{low}, a^i_{NE}]$, over which adaptation constraints benefit Bangladesh at the expense of the US. Using equation (3.32), the same result holds for negative marginal benefit shocks when the initial adaptation level in Bangladesh is sufficiently low.

Given such results, an important question involves the net change in payoffs. When will the gains to country i exceed the losses to its opponent? Manipulation of equations (3.22) and (3.32) shows that for $d\Pi^i_{NE} > -d\Pi^{-i}_{NE}$ it must be that

$$B^i_1\left[\frac{\partial m^{-i}_{NE}}{\partial \bar{a}^i}d\bar{a}^i + \frac{\partial m^{-i}_{NE}}{\partial \bar{a}^{-i}}d\bar{a}^{-i}\right] + \frac{\partial \Pi^i}{\partial a^i}d\bar{a}^i > -B^{-i}_1\left[\frac{\partial m^{i}_{NE}}{\partial \bar{a}^i}d\bar{a}^i + \frac{\partial m^{i}_{NE}}{\partial \bar{a}^{-i}}d\bar{a}^{-i}\right] - \frac{\partial \Pi^{-i}}{\partial a^{-i}}d\bar{a}^{-i} \quad (3.44)$$

$$B^i_1\left[\frac{\partial m^{-i}_{NE}}{\partial Z^i}dZ^i + \frac{\partial m^{-i}_{NE}}{\partial Z^{-i}}dZ^{-i}\right] + a^i_{NE}dZ^i > -B^{-i}_1\left[\frac{\partial m^{i}_{NE}}{\partial Z^i}dZ^i + \frac{\partial m^{i}_{NE}}{\partial Z^{-i}}dZ^{-i}\right] - a^{-i}_{NE}dZ^{-i} \quad (3.45)$$

where equations (3.44) and (3.45) are the conditions for the constraint and shock scenarios, respectively. A necessary condition for each to hold is that

$$B^i_1 dm^{-i}_{NE} > -B^{-i}_1 dm^i_{NE} \quad (3.46)$$

That is, the first-order approximation of the benefit to country i of increased mitigation from $-i$ must exceed the same approximated loss to country $-i$. Since the slope of any country's mitigation best-response curve must be $\in (-1, 0)$, examination of Figure 3.2 reveals that we must have $dm^{-i}_{NE} > -dm^i_{NE}$.[17] Therefore equation (3.46) will hold whenever $B^i_1 > B^{-i}_1$, evaluated at Nash equilibrium levels of mitigation and adaptation. In other words, the marginal benefit of mitigation for i must be greater than that for $-i$ when $dm^i_{NE} < 0$ and $dm^{-i}_{NE} > 0$. Since this is a necessary condition, there are other important factors. Namely, Nash equilibrium adaptation should be sufficiently low in both countries for the result to hold in the shock scenario, while the marginal benefits of adaptation must be sufficiently low for the constraint scenario. If equation (3.46) does not hold, then we can

[17] See equation (3.11) in the proof of proposition 2.

guarantee that the losses will exceed the gains.

As a simple example, suppose that the payoffs for H and F are defined as

$$\begin{aligned}\Pi^H &= 2.5\Big[110 - (m^H + m^F)\Big](m^H + m^F) + 2.5(25 - a^H)a^H \\ &\quad - (m^H + m^F)a^H - (m^H)^2 - (a^H)^2 + Z^H a^H \qquad (3.47)\\ \Pi^F &= 2\Big[110 - (m^H + m^F)\Big](m^H + m^F) + 1.75(124 - a^F)a^F \\ &\quad - 3.5(m^H + m^F)a^F - (m^F)^2 - (a^F)^2 + Z^F a^F \qquad (3.48)\end{aligned}$$

where $B_{11}^H = B_{22}^H = -5$, $B_{11}^F = -4$, $B_{22}^F = -\frac{49}{16}$, $B_{12}^H = -1$, and $B_{12}^F = -3.5$ for all combinations of $(m^i + m^{-i}, a^i)$. Hence, country H is both less effective at adapting and more sensitive to climate change. In the analogy above, country H is Bangladesh and country F is the US.

In Figure 3.6, Nash equilibrium payoffs and mitigation are plotted over different levels of the constraint, where $Z^i = 0$ for all i. In this example, the constraints are set (and reduced) at the same rate for each country as a percentage of unconstrained adaptation. However, unconstrained adaptation is less in country H (3.17 versus 13.79 in country F), and therefore in nominal terms, $d\bar{a}^F < d\bar{a}^H$ as you move right to left in both sub-figures.[18]

Figure 3.7, on the other hand, presents Nash equilibrium outcomes for different shocks to the marginal benefit of adaptation, as represented by Z^i in equations (3.47) and (3.48). Here we assume that $Z^H = Z^F$ and therefore, $dZ^H = dZ^F < 0$ as you move right to left.

In both scenarios, we see that m_{NE}^F rises and m_{NE}^H falls whether the constraint is tightened or the shock to marginal benefits becomes more negative. In the constraint scenario, this is sufficient to guarantee at least an interval over which payoffs for H increase at the expense of country F. In fact, this interval contains $a^H = a^F = 0$; H is increasingly better off in Nash equilibrium the more adaptation is constrained, while F is increasingly worse off.

In the shock scenario, we must also consider the direct effect of the shock. However, since a_{NE}^H is low to begin with, the gain from foreign mitigation outweighs the direct effect for H. Again, payoffs rise for H and fall for F as the shocks gets more negative.

In both the constraint and shock examples, the gains to country H exceed the losses to F. However, as discussed above, it is not hard to construct examples where losses exceed gains.

[18] However, both countries reach the constraint $d\bar{a}^F = d\bar{a}^H = 0$ at the same moment.

3.5 Conclusion

In this paper, we have extended the Hoel (1991) model of climate change to include adaptation as a strategic choice variable for each country. We have shown how the ability to adapt reduces the incentive to mitigate since adaptation and mitigation are substitutes domestically. And since countries trade-off mitigation internationally, adaptation in one country effectively harms others through increased emissions and higher costs of intervention.

We have illustrated how the strategic effects can lead to situations in which one or both countries are better off when adaptation is restricted. The two scenarios we use to motivate these results are a negative shock to the marginal benefit of adaptation and a direct constraint on adaptation, noting that a tax with lump-sum refunds can replicate the results of the constraint.

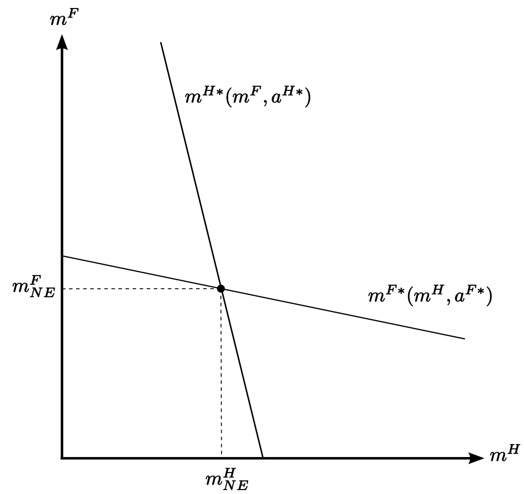
We are not advocating that countries entirely resist the urge to adapt. Clearly, adaptation will be extremely important for the preservation and survival of some regions. However, a blind reliance on our ability to adapt also seems misplaced, especially when we consider the strategic nature of mitigation as a global public good and the fact that resources used to invest in adaptation might also have been used to mitigate.

While the strategic interactions imply that any single country is unlikely to unilaterally limit its adaptation, a multilateral agreement might be possible if countries could be persuaded together. Our results have shown that in many cases, payoff-improving intervals of adaptation constraints (or taxes) do exist.

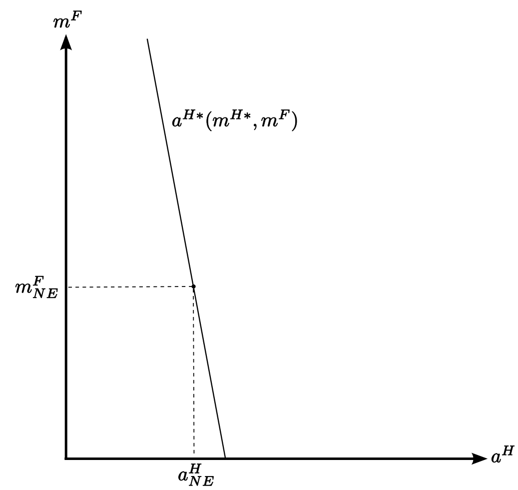
Although interest in adaptation to climate change is rapidly growing, there is still a tendency in academic and policy circles to focus discussion mostly, if not entirely, on mitigation. In some respects, this is not surprising. Since adaptation provides a private benefit, the marginal conditions for optimization are the same whether we are interested in the Nash equilibrium or a social optimum. Thus, most intellectual thought considers solutions to the global public goods aspect of mitigation and how to manage the externality of emissions. However, the substitute nature of mitigation and adaptation implies that adaptation should have a role in any optimal tax arrangement, at least from a theoretical point of view. On a more general level, if we do not account for the incentive to adapt, any attempt to identify preferred outcomes will be misguided. We will, in other words, target a level of emissions that is not socially optimal.

Figure 3.1: Best-Response Curves & the Nash Equilibrium

(a) Mitigation



(b) Adaptation in Country H



(c) Adaptation in Country F

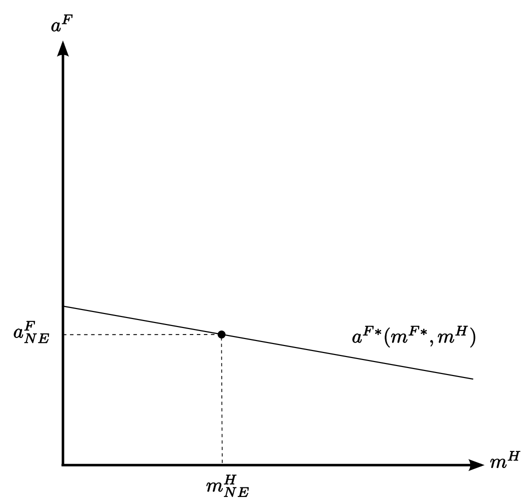


Figure 3.2: Comparison of Nash equilibrium outcomes in games with and without adaptation

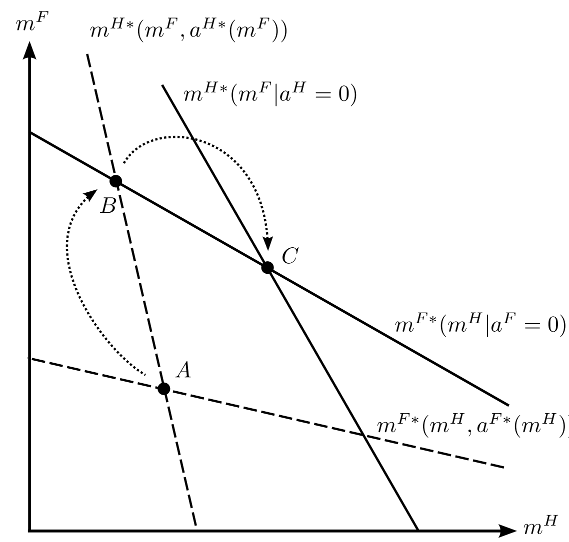


Figure 3.3: Constrained Adaptation — Example 1

(a) NE Payoffs (b) NE Mitigation

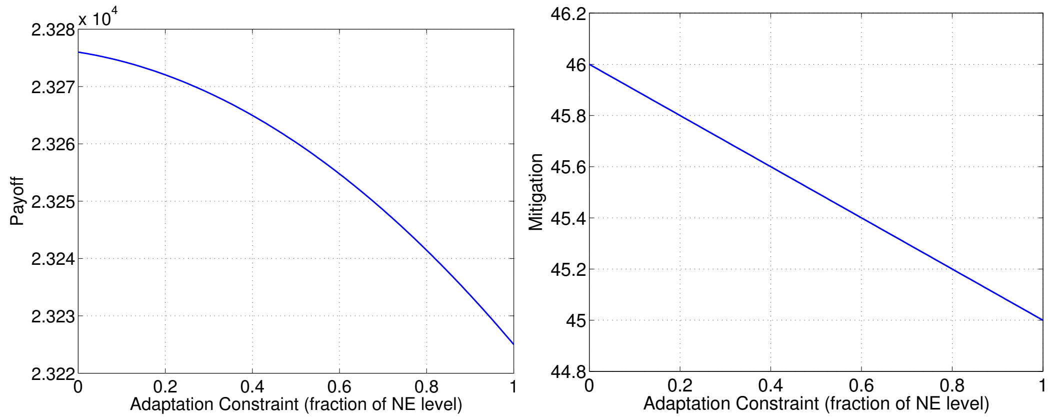


Figure 3.4: Constrained Adaptation - Example 2

(a) NE Payoffs (b) NE Mitigation

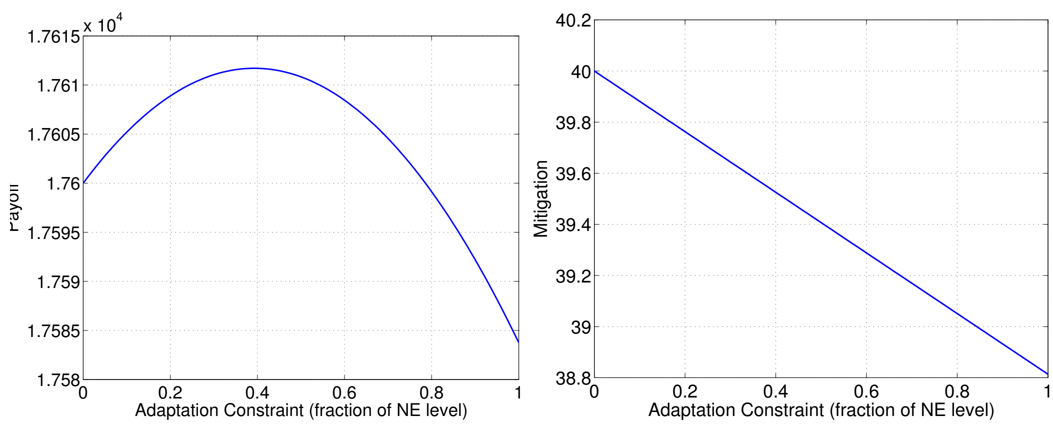
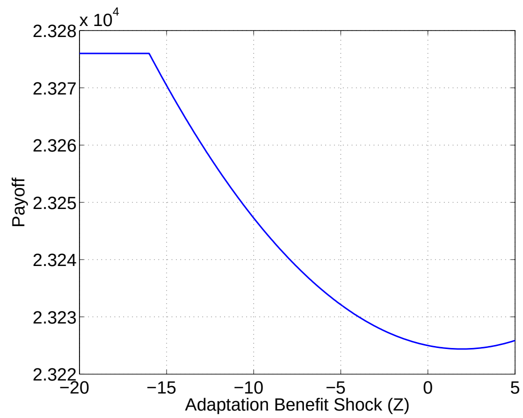
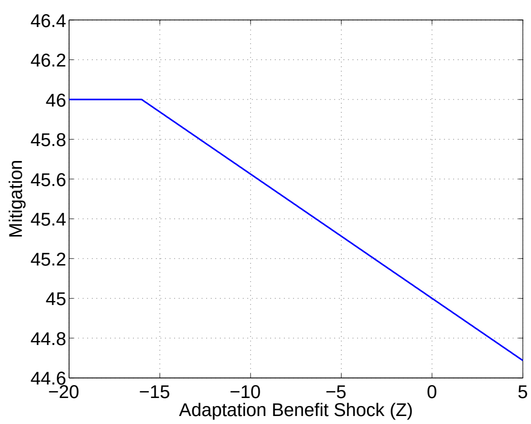


Figure 3.5: Shocks to the Marginal Benefit of Adaptation

(a) NE payoffs



(b) NE mitigation



(c) NE adaptation

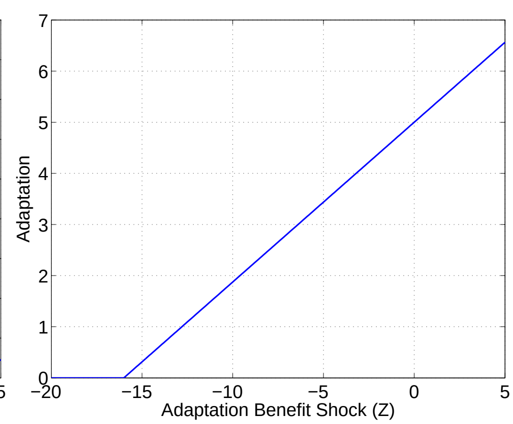
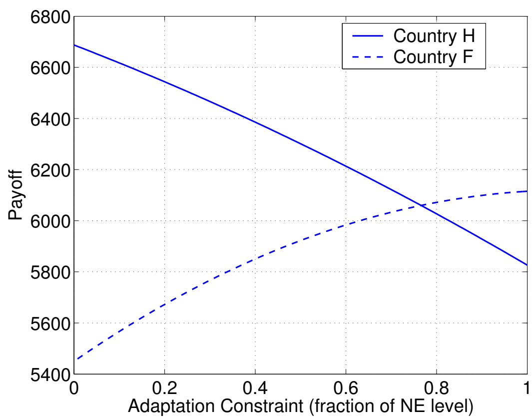


Figure 3.6: Heterogeneous Countries with Constrained Adaptation

(a) NE payoffs



(b) NE mitigation

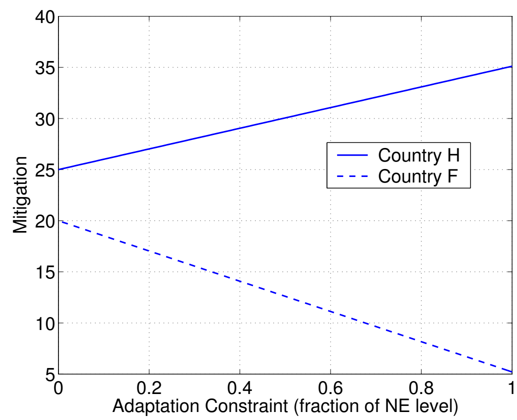
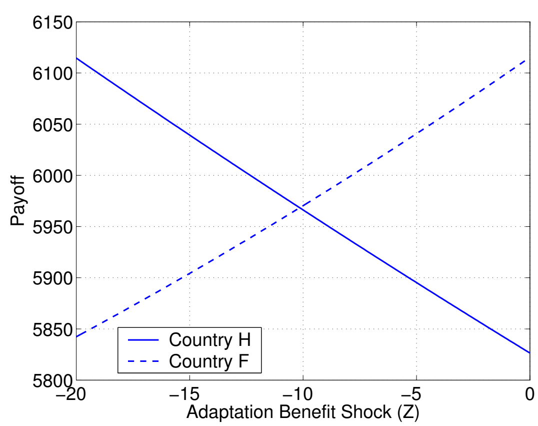
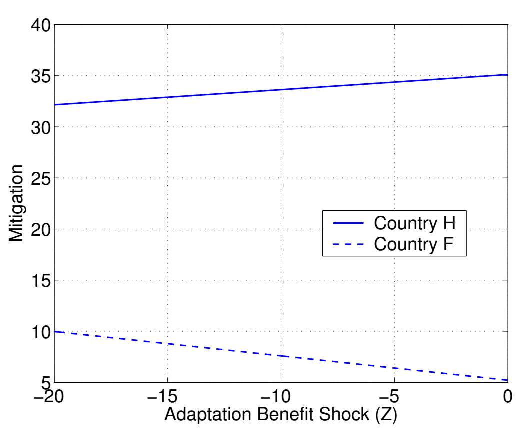


Figure 3.7: Heterogeneous Countries with Benefit Shocks

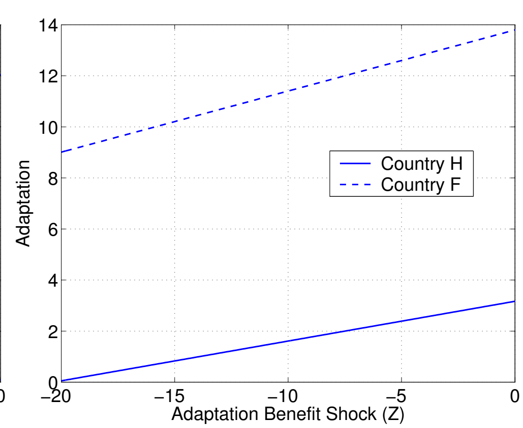
(a) NE payoffs



(b) NE mitigation



(c) NE adaptation



APPENDIX A

Should net-returns be included in the models of land use change?

In the context of estimating treatment effects, bad control occurs when the researcher includes additional explanatory variables that are themselves potential outcome variables with respect to treatment.[1] In other words, the variables termed "bad controls" could also be regarded as possible dependent variables.

Might the net-return variables used in existing land-use models be bad controls when climate is also included? As a useful example, consider that Ricardian models of agricultural adaptation to climate change (Mendelsohn et al., 1994; Schlenker et al., 2006) motivate their dependent variable, farmland value, as the present-discounted stream of future net-returns, which is then regressed on climate. They are explicitly estimating the causal effect of climate on net-returns.

In the multinomial models of land use derived from Lubowski (2002)[2], net-return variables are generally constructed as

$$\text{Net Returns} = (\text{price} * \text{yield}) - \text{costs} \tag{A.1}$$

Changes in climate (i.e., average weather) are likely to have a direct effect on yield for any given land use, as shown in Burke and Emerick (2016) for the case of corn. Furthermore, changes in climate might have indirect effects on prices and input costs in local markets through feedback effects from changes in yield. This suggests that all of the components of the net-returns variable can be viewed as endogenous to changes in climate. This problem is explored below using a simple model.

[1] See section 3.2.3 of Angrist and Pischke (2009) for a discussion of the "bad control" problem. Dell et al. (2014) also discuss the bad-control problem in the context of climate-change economics.

[2] See e.g., Lubowski et al. (2006, 2008); Radeloff et al. (2012); Haim et al. (2011); Hamilton et al. (2013).

A.1 A simple climate model to illustrate bad control

Suppose that landowners have two options: pasture and cropland.[3] Assume also that local prices for crops take one of two values: "low" or "high". Let y_i be a dummy variable representing the choice of cropland, and let p_i be a dummy variable for "high" prices.

Climate change is also a binary outcome in this model, where $c_i = 1$ for locations that experience a change in climate, and $c_i = 0$ otherwise. Climate change can affect the realization of both y_i and p_i. However, we assume that climate change itself is randomly assigned. This implies that whether or not a location experiences climate change is independent of its potential outcomes, and therefore, average treatment effects on both y and p could be estimated by regressing only on c.

Let y_{1i} and y_{0i} represent potential land use outcomes in location i when $c_i = 1$ and 0, respectively. We adopt a similar definition for p_{1i} and p_{0i}. Suppose that we are concerned about omitted variable bias, and we decide to include p_i as a control since a high crop price can impact the decision to convert to cropland, and prices are likely correlated with changes in climate. Holding prices fixed at "high" levels, we estimate the difference in the probability of switching to cropland between locations that experience climate change and those that do not by computing

$$\mathbb{E}\left[y_{1i}|p_{1i}=1, c_i=1\right] - \mathbb{E}\left[y_{0i}|p_{0i}=1, c_i=0\right] \tag{A.2}$$

Since changes in climate are assigned randomly, equation A.2 is equivalent to

$$\mathbb{E}\left[y_{1i}|p_{1i}=1\right] - \mathbb{E}\left[y_{0i}|p_{0i}=1\right] \tag{A.3}$$

which, by adding and subtracting $\mathbb{E}\left[y_{0i}|p_{1i}=1\right]$, we can rewrite as

$$\mathbb{E}\left[y_{1i}-y_{0i}|p_{1i}=1\right] + \left\{\mathbb{E}\left[y_{0i}|p_{1i}=1\right] - \mathbb{E}\left[y_{0i}|p_{0i}=1\right]\right\} \tag{A.4}$$

The first term represents the true desired causal effect of climate change for locations that also experience high prices under climate change. The second term, $\{\cdot\}$, is selection bias, and is likely negative in this simple model. Considering $\mathbb{E}\left[y_{0i}|p_{0i}=1\right]$, areas that have high prices in the absence of climate change also probably have higher than average cropland shares. If we condition instead on high prices when climate change occurs, $\mathbb{E}\left[y_{0i}|p_{1i}=1\right]$, then for some i, it may be that $p_{1i}=1$ while $p_{0i}=0$. On average, we might expect that $\mathbb{E}\left[y_{0i}|p_{0i}=1\right] > \mathbb{E}\left[y_{0i}|p_{0i}=0\right]$, which would imply that the $\{\cdot\}$ term is neg-

[3] This closely follows the example from Angrist and Pischke (2009) on pp 64-66 and uses similar notation.

ative, though the magnitude would depend on the fraction of locations for which $p_{1i} = 1$ and $p_{0i} = 0$ as well as the difference in expected y_{0i}. In the full model with additional land uses, we might not be able to sign the bias if developed areas have higher than average prices, but low cropland shares.

The point of this exercise is to explicitly show how including net-returns to avoid omitted variables bias might instead create a bad control problem. As discussed in the parallel example in Angrist and Pischke (2009), even if there is no effect of climate change on land use ($y_{1i} = y_{0i}$), we will generally not find this from the model that includes net-returns. And if changes in climate are randomly assigned, as is likely the case, then there is no need to control for net-returns anyway.

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