Evaluating Policy Options to Reduce N_2O Emissions from US Agriculture

Richard Klotz[1], Antonio M. Bento

Cornell University

Ram Gurung, Stephen Ogle, Keith Paustian, John Sheehan

Colorado State University

[1] Corresponding Author: rlk99@cornell.edu

Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28

Evaluating Policy Options to Reduce N_2O Emissions from US Agriculture*

Richard Klotz† Antonio M. Bento Ram Gurung Stephen Ogle

Keith Paustian John Sheehan

May 27, 2015

*****Preliminary and Incomplete*****

Please Do Not Cite

Abstract

If emissions from a sector are unobservable, direct emissions policies are unlikely to be extended to this sector. However, alternative policies based on observable quantities may be able to reduce emissions from the unregulated source at costs similar to a first-best policy. This paper evaluates the costs of policy instruments for reducing GHG emissions from cropland agriculture, a large source of emissions that are unobservable, using an integrated biophysical and economic model. Results suggest that policies regulating readily observable quantities can reduce agricultural N_2O emissions at costs approaching those of the unavailable emissions tax. However, alternative policies with costs similar to the emissions tax may have considerably different impacts on agricultural sector profit.

*This project was supported by Agriculture and Food Research Initiative Competitive Grant no. 2011-67003-30205 from the USDA National Institute of Food and Agriculture.

†Klotz (corresponding author): 438 Warren Hall, Charles H. Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY 14850; rlk99@cornell.edu. Bento: Cornell University. Gurung, Ogle, Paustian, Sheehan: Colorado State University.

1 Introduction

To efficiently regulate a global pollutant, the marginal costs of abatement must be equalized across all emitting sources. Yet, proposed and enacted climate change regulations violate this principle by leaving sectors that are significant contributors of greenhouse gas (GHG) emissions unregulated. A prominent justification for leaving a sector unregulated is that emissions are unobservable. If a sector's emissions are unobservable or are prohibitively costly to monitor then direct emissions regulations, such as a carbon tax or cap and trade program, might be impossible or too costly to extend to the unregulated sector. Alternative policies based on readily observable quantities that reduce emissions from the unregulated sector at costs similar to the first-best could lower the overall costs of climate action.

In this paper, we explore whether policy instruments based on observable quantities can cost-effectively reduce GHG emissions from cropland agriculture in the US. Cropland agriculture contributes 12% of annual global emissions (IPCC, 2014) and 8% of annual US emissions (US EPA, 2014), but is typically exempt from climate legislation. The exclusion of agriculture is partly the result of monitoring difficulties. GHG emissions from agriculture depend on the production decisions of many farmers facing heterogeneous weather and soil characteristics. Absent field-level monitoring, agricultural emissions are unobservable and cannot be directly regulated.

We focus on agricultural nitrous oxide (N_2O) emissions, which is the single largest component of GHGs from agriculture (US EPA, 2014). We use analytical and numerical general equilibrium models to evaluate the costs of emissions reductions using a range of policy options. The analytical model allows me to decompose the costs associated with a marginal change in a policy, while the numerical model allows me to quantify the differences in costs across policies for large reductions in emissions. The numerical model is a national-scale integrated biophysical and general equilibrium framework that accounts for agricultural production decisions at the county level and how changes in farm-level behavior will impact crop and food prices and consumer decisions at the national level. The framework captures the primary channels through which farmer decisions affect N_2O emissions, crop choice and nitrogen (N) fertilizer application rates. In each county, a representative landowner maximizes profits by choosing an N fertilizer application rate for, and an amount of land to allocate to, each crop. The relationships between agricultural decisions, crop yield and emissions are estimated from a unique data set of biophysical model simulations that allow for heterogeneity in production characteristics, a key driver of the performance of alternative policies, at a fine spatial scale. Using this framework, we calculate the welfare costs of achieving targeted levels of emissions reductions using an N_2O tax, uniform and non-uniform input taxes and acreage taxes, as well as combinations of these policies. The optimal policy instruments are solved for using a Mathematical Programming with Equilibrium Constraints

(MPEC) formulation.

Preliminary results suggest that the unavailable N_2O tax can reduce total N_2O emissions by 2.5% at a marginal cost of just over 60 \$/tCO_2e. The simplest alternative policy, a uniform N tax, is 40% more costly than the N_2O tax, because it does not account for heterogeneity in marginal emissions rates across crops or space. However, both non-uniform instruments and combinations of instruments can be used to achieve emissions reductions at costs similar to the N_2O tax. A non-uniform N tax, that varies by region to account for some of the heterogeneity in marginal emissions across space, provides N_2O reductions at costs only 10% higher than the emissions tax. Pairing the uniform and non-uniform N taxes with acreage taxes reduce costs by providing a direct mechanism by which to control the amount of land in emissions intensive crops. However, the cost savings, relative to the N taxes alone, due to the addition of acreage taxes are small. Even though the alternative policies can result in costs similar to the emissions tax, there are considerable differences in the impacts on profits of the agricultural sector. The impact of the N taxes on profits are only 20% that of the emissions tax. In sharp contrast, pairing acreage taxes with the N taxes causes profits to fall by more than under the emissions tax. These results raise questions about second-best combinations of policies if the welfare of the regulated sector is a political concern.

1.1 Literature Review

When emissions are unobservable, the theoretical literature suggests that a range of policies based on observable quantities could be applicable.[1] Many authors provide motivation for taxing goods related to emissions (for example Green and Sheshinski (1976) or Sandmo (1978)), but policies that are able to control all channels through which emissions can be reduced can be more cost-effective. When there are a large number of heterogeneous pollution sources, non-uniform or multipart instruments (Fullerton and West, 2002) and regulations based on modeled emissions (Griffin and Bromley, 1982) are likely to be more efficient than single, uniform regulations of observable factors. In fact, first-best outcomes can be achieved with sufficiently differentiated tax rates, complex multipart instruments or perfect models of emissions, but may be impractical due to extreme information requirements, high implementation costs and avoidance behavior. The theoretical literature does not provided general conclusions about the performance of second-best policies, so ranking alternative instruments requires a numerical analysis (Helfand and House, 1995; Fullerton and Gan, 2005; Fullerton and West, 2010; Knittel and Sandler, 2013). To our knowledge, this is the first comparison of the costs of alternative policy instruments for GHG mitigation in US agriculture at the national-scale.

[1] The inability to observe emissions is a key feature of research on the regulation on non-point source pollution from agriculture, see Shortle and Horan (2001) or Xepapadeas (2011) for reviews of this literature. Non-point source pollution regulations must also address marginal damages varying across sources, but may be able to exploit observable ambient pollution levels (Segerson, 1988).

This paper builds on the long literature assessing the costs of GHG mitigation in the agricultural sector. One group of studies on agricultural mitigation use national-scale using linear programming models (McCarl and Schneider, 2001; De Cara and Jayet, 2000; De Cara et al., 2005). McCarl and Schneider (2001), the most prominent of these studies, assesses a host of mitigation options for US agriculture and forestry, including agricultural management options such as tillage, crop, and input intensity choices, as well as biofuels and afforestation. A limitation of these models is that each relies on simplified relationships between management options, yields and emissions. For example, N fertilizer application rates are constant in De Cara and Jayet (2000) and De Cara et al. (2005), and McCarl and Schneider (2001) allow for discrete choices of N application rates. Moreover, the relationship between activities and emissions are captured using IPCC default methods (IPCC, 1997; IPCC, 2006), which rely on a linear relationship between N applications and N_2O and may not capture the significant heterogeneity in N_2O emissions due to soil and climate characteristics.[2] The heterogeneity of yield and emissions responses to management changes plays a critical role in determining the performance and availability of mitigation policy options. Another group of studies accounts for this heterogeneity by integrating biophysical and economic models (Antle et al., 2003, 2007; Garnache et al., 2014), with biophysical models providing detailed information regarding yield and emissions responses. Due to the complexities involved with such frameworks, the linked biophysical and economic models focus on small regions or a limited number of management options.

Our work extends this previous literature along two dimensions. First, we construct a linked biophysical and economic model at the national level that accounts for heterogeneity in yield and emissions responses at a fine spatial scale. Therefore, the model can capture how heterogeneity affects the performance of national level policies, which is crucial in the context of N_2O, and the impact of mitigation policies on other national level outcomes, such as the price of crops and food. Second, unlike most previous work, which either assumes that emissions can be directly regulated (McCarl and Schneider, 2001; De Cara and Jayet, 2000; De Cara et al., 2005; Antle et al., 2007) or analyzed practice-based subsidies (Antle et al., 2003), we analyze a variety of policy options suited to addressing unobservable emissions. Therefore, we are able to provide more meaningful estimates for the costs of harnessing the mitigation potential of agriculture and insights regarding the design of policies in this context.

The previous work most similar to the current study is a set of recent papers that develop a detailed linked biophysical and economic model of cropping for the Central Valley of California (Mérel et al., 2014; Garnache et al., 2014). The model accounts for changes in input use, nitrogen fertilizer and irrigation water, and cropping patterns. Mérel et al. (2014) outlines the numerical framework and the procedure for

[2]The modeling framework used in McCarl and Schneider (2001) has been updated to include biophysical model estimates of N_2O (Ogle et al., 2015).

calibrating to baseline economic data and biophysical model output, then analyzes reductions in N_2O and nitrate pollution due to a uniform tax on N. Garnache et al. (2014) compare the costs of agricultural GHG mitigation, accounting for CO_2, N_2O and CH_4, using policy options that can be implemented when emissions are unobservable. Relative to Garnache et al. (2014), we consider a broader set of policies, including acreage taxes, and combinations of policies. In addition, since our framework is national in scale we have a setting where spatial heterogeneity and differentiated policies may be of more importance. However, unlike Garnache et al. (2014) we only account for N_2O and do not account for changes in irrigation intensity.

The remainder of the paper is organized as follows. Section 2 provides background on GHGs from cropland agriculture paying particular attention to the determinants of N_2O emissions. Section 3 lays out the analytical model and decomposes the marginal primary costs of an N_2O tax and alternative policy options. The structure of the numerical model and the data used for calibration are presented in Sections 4 and 5. Simulation results from the numerical model are presented Section 6 and Section 7 concludes.

2 Background

2.1 Agriculture and GHGs

Agriculture is a substantial source of GHG emissions, making up roughly 12% of annual global emissions (IPCC, 2014) and roughly 8% of annual US emissions (US EPA, 2014).[3] If current trends in population and economic growth and food consumption persist, emissions from agriculture are projected to increase substantially in the coming decades (Popp et al., 2010; EPA, 2012).

Policymakers increasingly recognize the need to reduce emissions from agriculture. In the recent 5th Assessment Report the IPCC states, with high agreement, that: "leveraging the mitigation potential in the sector is extremely important in meeting emissions reductions targets" (IPCC, 2014). In California, the goal of establishing GHG reduction targets for agriculture was approved as part of the recent update to the Scoping Plan for AB 32, the Global Warming Solutions Act passed in 2006 (CARB, 2014). However, agriculture is typically exempt from climate legislation.[4]

A variety of activities contribute to agricultural GHG emissions. There is general agreement that soil management, which includes emissions attributable to cultivated organic soils, crop residues and the ap-

[3]According to IPCC (2014), agriculture, forestry and land use contribute 24% of global GHGs, about 10 $GtCO_2e$. Agricultural production comprises just over half of this total.

[4]Agriculture was uncapped in the Kyoto Protocol, but agricultural mitigation projects could have received payments through the Clean Development Mechanism and Joint Implementation programs. Proposed federal climate legislation in the United States has rarely covered agriculture, but provisions for agricultural offsets are generally supported by lawmakers (Johnson, 2009). For example, the American Clean Energy and Security Act of 2009, also known as the Waxman-Markey climate bill, would have allowed offsets to cover a substantial and increasing share of required emissions reductions, 26% in 2016 and 66% in 2050 (Yacobucci et al., 2009). Offsets from domestic agricultural projects would have contributed to this total.

plication of manure and synthetic fertilizer, and methane released due to enteric fermentation in ruminant animals, such as cattle, are the two largest agricultural sources of GHGs (IPCC, 2014).[5] Agricultural soils also contain large stocks of carbon. Changes in soil carbon stocks due to agricultural activities can be either a source or sink of GHGs (US EPA, 2014).[6]

2.2 Agricultural N_2O

This paper focus on emissions of nitrous oxide (N_2O) from cropland agriculture, which is a substantial contributor to emissions due to soil management. N_2O is a potent GHG that is roughly 300 times more powerful than CO_2 in terms of its global warming potential (GWP).[7] In the US, agricultural N_2O contributes more than half of emissions from agriculture and nearly 5% of total GHGs (US EPA, 2014). With the exception of GHG emissions from passenger vehicle transportation, which can be reasonably monitored through gasoline consumption statistics, N_2O from agriculture is the largest non-point source of GHG emissions in the US.[8] Over 90% of agricultural N_2O results from the application of fertilizer and manure to cropland soils.[9] As a result, there is strong interest in policy options that induce changes in farmer behavior to reduce N_2O (Robertson and Vitousek, 2009; Cavigelli et al., 2012; Reay et al., 2012; UNEP, 2013).

N_2O emissions are generated primarily due to agriculture's impact on the nitrogen (N) cycle.[10] N is a fundamental element for plant growth but is deficient in most intensive agricultural systems because the N removed in crop yields vastly outstrips the natural deposition of N to soils (Robertson and Vitousek, 2009). N, in the form of chemical fertilizer or manure, must therefore be applied to soils to sustain crop growth, particularly for non-leguminous crops (Erisman et al., 2008). However, not all N applied to agricultural soils is used by the crop. The availability of excess N in soils leads to a number of environmental problems, including elevated emissions of N_2O.[11] Excess N leads to N_2O directly and indirectly. Direct N_2O emissions

[5] Manure management and rice cultivation are the other two notable sources, but are far smaller in magnitude (IPCC, 2014).

[6] Soil carbon stock changes depend on a variety of factors including the state of land prior to its conversion to agriculture, management choices and climate and soil characteristics. In the US, cropland soils are currently a net carbon sink due to significant enrollment of land in the Conservation Reserve Program, the adoption of conservation tillage, increased hay production and reductions in summer fallow in semi-arid regions (US EPA, 2014).

[7] It is worth noting that the marginal social cost of N_2O may actually be higher than the GWP of N_2O times social cost of CO_2. Marten et al. (2015) find that when calculated in a manner consistent with estimates of the social cost of CO_2, the social cost of N_2O should be closer to 314-387 times the social cost of CO_2. Moreover, N_2O is currently the largest contributor to depletion of the ozone layer, primarily because it is unregulated by the Montreal Protocol (Ravishankara et al., 2009).

[8] For a sense of the relative importance, agricultural N_2O emissions are of the same magnitude as emissions from oil combustion by industrial sources and natural gas use by residential sources, and are larger than CO_2 from aviation and methane from livestock operations (US EPA, 2014).

[9] Direct and indirect emissions from cropland account for 70% of N_2O from US agriculture. The remainder is made up of emissions from grazed areas and manure management systems (US EPA, 2014)

[10] See Robertson and Vitousek (2009) or Cavigelli et al. (2012) for a detailed review of agriculture's role in the nitrogen cycle.

[11] Excess N that makes its way into water can cause algal blooms and hypoxic zones, such as the "Dead Zone" in the Gulf of Mexico, and can contribute to nitrate contamination of drinking water, which may affect human health (Powlson et al., 2008). If released to the air, N can increase levels of particulate matter and ground level ozone, both of which affect human respiratory and cardiovascular systems. Moreover, ammonia emissions and the deposition of N to downwind locations can affect the biodiversity of the affected ecosystems. See Sutton et al. (2011) for a summary of a large-scale study quantifying the costs of excess N in Europe.

are generated by microbial nitrification and denitrification processes in the soils where N is applied. Indirect N_2O emissions are generated when N is transported from the soils where it is applied in forms other than N_2O, through either volatilization or leaching and runoff, and subsequently converted to N_2O elsewhere. The volatilization channel accounts for N that is released from agricultural soils to the atmosphere as ammonia (NH_3) or nitrogen oxides (NOx) and is eventually deposited on other soils or water bodies. The leaching and runoff channel accounts for N that is transported from agricultural soils through the water table and then converted to N_2O through aquatic denitrification. Direct emissions are the major contributor to N_2O. Over 50% of US agricultural N_2O emissions are direct emissions from agricultural soils, while indirect N_2O emissions from agricultural soils make up roughly 20% (US EPA, 2014).

This work focuses solely on agricultural N_2O for two reasons. First, despite being the single largest source of GHGs from agriculture both in the US and globally, few studies directly analyze policy options to reduce agricultural N_2O at a national-scale.[12] This paper is an initial attempt to fill that gap in the literature. Second, although much attention has been payed to carbon sequestration in cropland soils (Antle et al., 2003; Sperow et al., 2003; UNEP, 2013) there are serious questions regarding the potential for changes in agricultural management to achieve permanent emissions reductions. For example, Powlson et al. (2014) note that much of the potential increase in soil carbon due to many years of reduced tillage intensity could be lost due to conventional tillage in a single year, a common practice in some regions.[13] Moreover, soils have a limited capacity to store carbon. While shifts in management may result in increased soil sequestration for a number of years, the sequestration rate will fall to zero as soil carbon approaches equilibrium levels (Powlson et al., 2014). In contrast, N_2O reductions are permanent, irreversible and can be realized in perpetuity.

Determinants of N_2O Emissions

N_2O emissions from cropland agriculture depend on the production decisions of many farmers operating under diverse soil and weather conditions. Cropland N_2O emissions largely depend on the level of excess N in soils, which is roughly the difference between N additions and N uptake by the crop. The rate at which excess N is converted to N_2O depends on the biophysical conditions of the soil, such as soil texture, moisture and temperature (Robertson and Groffman, 2015). Farmers' choices affect N_2O emissions either by altering excess N or the biophysical conditions in soil (Parkin and Kaspar, 2006). Farmers' choice of crop, because N uptake rates differ by crop, and N additions are the key determinants of excess N (Eagle et al., 2012).[14]

[12]Note that McCarl and Schneider (2001) includes N_2O in the analysis, but does not engage with the observability problem. Garnache et al. (2014) and Horowitz (2014) explore policies to reduce N_2O but only for a small region.

[13]Powlson et al. (2014) also emphasize that experimental and model evidence does not necessarily support the claim that reductions in tillage intensity will result in increased carbon stocks.

[14]Timing and placement of N additions are also choices that affect excess N (see Eagle et al. (2012) for a review). Placing N closer to the active root zone of the plant lowers the availability of N for conversion to N_2O. N demands of a crop vary across the growing season, which creates a temporal dimension of excess N. Timing N applications to match periods of high N demand

Irrigation and tillage are examples of management choices that change soil conditions and alter N_2O emission rates.

All else equal, soil characteristics and climate/weather lead to considerable spatial heterogeneity in cropland N_2O emissions rates (Del Grosso et al., 2006, 2012). Using Daycent, Del Grosso et al. (2012), find that N_2O emissions rates, the percent of N applied released as N_2O, tend to be highest for soils that are fine textured, high in organic matter and wet, either due to precipitation or irrigation. In fact, the differences in emissions rates across fields with different characteristics but the same N input levels, can be more substantial than differences due to N application rates in the same field (Del Grosso et al., 2006). Even within field differences in emissions can be quite large (Parkin, 1987). The management decisions and soil conditions that impact N_2O rates also affect the returns to cropland through yields and production costs (Balasubramanian et al., 2004). The resulting differences in farmers' management choices are an additional driver of variation in N_2O emissions. Moreover, heterogeneity in the marginal costs of abatement is determined by differences in the tradeoff between emissions and returns to cropland across fields. Table A.4 displays the heterogeneity across crops and regions in baseline N_2O rates used in this analysis.

Monitoring N_2O Emissions

Due to the nature of the emissions generation process, wide-scale monitoring N_2O emissions is difficult with current technology. Monitoring must take place at a fine spatial and temporal resolution to account for the heterogeneity in emissions rates, the influence of the management decisions of many individual farmers and the temporal distribution of emissions.[15] Measurements from static chambers on cropland is the current economical monitoring option for experimental observation. However, using these methods in a national monitoring program would be infeasible because the measurements are limited to the conditions underneath the chamber and the specific measurement period (Hensen et al., 2013). Avoidance behavior could also be problematic.[16] New approaches, relying on micrometeorological methods and infrared technology, are being developed that could provide more frequent measurements at the farm-scale, but are not yet available at reasonable costs (Hensen et al., 2013).

by the crop can therefore reduce N_2O emissions. Eagle et al. (2012) also note that the type of fertilizer used, particularly slow release types and those with nitrification inhibitors, may affect N_2O emissions.

[15] N_2O is emitted throughout the year, but rates are typically highest immediately following fertilizer applications (see for example Hoben et al. (2011)). A monitoring system that does not measure emissions during these periods could significantly underestimate emissions.

[16] For example, less N fertilizer could be applied to the area under and immediately surrounding the chamber or fertilizer could be applied immediately after a chamber measurement is taken.

3 Analytical Model

This section presents an analytical model that decomposes the primary costs resulting from a marginal change in policy options to reduce agricultural N_2O. An emissions tax, a uniform input tax and crop acreage taxes are considered. Policy options were selected under the assumption that the regulator observes the total quantity of inputs purchased for use on each parcel and the allocation of land in each parcel. These quantities can be observed at very low cost since commercial fertilizer distributors must be registered through state control boards, and land allocation at the field level are obtainable through existing remote sensing efforts (NASS, 2014a). The regulator is assumed to be unable to observe input quantities applied to each crop, because it would require tracking inputs between its purchase and use, monitoring field-level activities or accurate self-reporting. This rules out any policy that regulates inputs applied to a particular crop, such as an input tax differentiated by crop.

3.1 Framework

General Environment

Consider a static model of an economy with two factors of production, labor ($\bar{L}$) and land ($\bar{A}$). Labor is perfectly mobile, while land is immobile. The land endowment in divided into I regions indexed $i = 1 \ldots I$. Within each region there are J_i heterogeneous parcels of various sizes, indexed $j = 1 \ldots J_i$. The total land area available in each parcel is given by $\bar{A}_{ij}$. Land is combined with polluting and intermediate inputs to produce K crops indexed $k = 1 \ldots K$. Pollution emissions (E) are generated by the production of crops, with marginal emissions varying by crop, region and parcel and with the use of intermediate inputs. All markets are assumed to be perfectly competitive. The wage rate is normalize to 1.

Demand

A representative consumer derives utility from the K crops, denoted by C_k, and a composite consumption good C, and is harmed by emissions. The representative consumer's utility function is given by:

$$U\left(C_1, \ldots C_K, C\right) - \phi\left(E\right) \tag{1}$$

where $U(\cdot)$ is the utility from consumption and ϕ is the disutility from emissions. U is continuous, differentiable and strictly quasi-concave in all its inputs, and ϕ is continuous, differentiable and weakly convex.

The representative consumer's income comprises the returns to the labor and land (Π_A) endowments and a transfer from the government, G:

$$\sum_k P_k C_k + C = \Pi_A + \bar{L} + G \tag{2}$$

where P_k is the price of crop k. The consumer chooses C_k and C to maximize utility subject to the budget constraint but does not account for their effect on emissions when making consumption choices. Solving the resulting first-order conditions yield the uncompensated demand functions:

$$\begin{aligned} &C_k\left(P_1 \ldots P_K, \Pi_A, G\right) \quad \forall\, k \in K \\ &C\left(P_1 \ldots P_K, \Pi_A, G\right) \end{aligned} \tag{3}$$

which when substituted into (1) yields the indirect utility function:

$$V = v\left(P_1 \ldots P_K, \Pi_A, G\right) - \phi(E). \tag{4}$$

Production

Each parcel of land is independently managed to maximize profits by a risk neutral representative landowner. Per unit productivity and emissions of land is heterogeneous across crops and parcels, and assumed to be constant per unit land in a given parcel. The landowner chooses the quantity of land to allocate to each crop, A_{ijk}, and can also influence productivity and emissions using intermediate inputs. Let productivity and emissions per unit land be:[17]

$$y_{ijk}\left(n_{ijk}, m_{ijk}\right) \quad e_{ijk}\left(n_{ijk}, m_{ijk}\right) \tag{5}$$

where n_{ijk} and m_{ijk} are quantities of intermediate inputs N and M used in crop production. y_{ijk} and e_{ijk} are assumed to be continuously differentiable. N is a polluting input that boosts productivity, at a decreasing rate, and increases emissions rates. M is a mitigating input that reduces marginal emissions.[18] In the context of agriculture, one can think of y as crop yields, N as nitrogen fertilizer and M as mitigation options such as changes in the timing and placement of fertilizer or the use of nitrogen inhibitors.

Labor used for each parcel's production of crops is made up of two components, a fixed labor requirement per unit of land allocated to each crop, l_{ijk}, and management costs that depend on the parcel's land allocation, $L_{ij}\left(A_{ij1}, \ldots, A_{ijK}\right)$. These land management cost functions reflect factors other than net returns, such as

[17] Unless otherwise noted, lowercase letters represent quantities per unit land, while capital letters represent total quantities.

[18] Formally $\frac{\partial y_{ijk}}{\partial n_{ijk}} > 0$, $\frac{\partial^2 y_{ijk}}{\partial n_{ijk}^2} < 0$, $\frac{\partial e_{ijk}}{\partial n_{ijk}} > 0$ and $\frac{\partial e_{ijk}}{\partial m_{ijk}} < 0$.

land quality, that induce diversification of crop production within parcels.

To simplify notation denote $\boldsymbol{A}_{ij}$, $\boldsymbol{n}_{ij}$ and $\boldsymbol{m}_{ij}$ as vectors of length K that represent the land allocation and per unit land input usage for parcel ij.[19] On each parcel, the landowner chooses a land allocation and input vectors to maximize profit subject to a land constraint:

$$\begin{aligned}
\Pi_{ij}\left(P_1 \ldots P_K, P_N, P_M\right) = \max_{\boldsymbol{A}_{ij}, \boldsymbol{n}_{ij}, \boldsymbol{m}_{ij}} & \sum_k \pi_{ijk} A_{ijk} - L_{ij}\left(A_{ij1}, \ldots, A_{ijK}\right) \\
& \text{subject to:} \\
& \pi_{ijk} = P_k y_{ijk} - P_N n_{ijk} - P_M m_{ijk} - l_{ijk} \quad \forall\, k \in K \\
& \sum_k A_{ijk} \leq \bar{A}_{ij}
\end{aligned} \tag{6}$$

where π_{ijk} is the net returns per unit land to crop k in parcel ij.

The solution to each landowner's problem yields the optimal land allocation, $\boldsymbol{A}_{ij}\left(P_1 \ldots P_K, P_N, P_M\right)$, and per unit land input demands, $\boldsymbol{n}_{ij}\left(P_1 \ldots P_K, P_N, P_M\right)$ and $\boldsymbol{m}_{ij}\left(P_1 \ldots P_K, P_N, P_M\right)$. These functions then determine the total supply of crop k is $Y_k = \sum_{ij} y_{ijk}\left(n_{ijk}, m_{ijk}\right) A_{ijk}$, total emissions are $E = \sum_{ijk} e_{ijk}\left(n_{ijk}, m_{ijk}\right) A_{ijk}$ and total labor used for crop production is $L_A = \sum_{ijk} A_{ijk} l_{ijk} + \sum_{ij} L_{ij}$.[20]

Finally, the intermediate inputs and the composite consumption good are produced from labor and are denoted in units so that the marginal productivity of labor in each sector is equal to one ($N = L$, $M = L$, $C = L$). This establishes $P_L = P_N = P_M = 1$.

Government

The government sets policies to reduce total emissions. Any revenues generated by the pollution policies will be rebated to the representative consumer through G.[21]

Equilibrium

Equilibrium is a set of crop prices P_k such that profits to the land endowment and utility are maximized and the crop and labor markets clear:

$$\begin{aligned}
C_k &= Y_k \quad \forall k \in K \\
\bar{L} &= C + M + N + L_A.
\end{aligned} \tag{7}$$

[19] For example, $\boldsymbol{A}_{ij} = \left\{A_{ij1} \ldots A_{ijK}\right\}$.

[20] Total use of the intermediate inputs and total returns to land can be calculated with similar formulas. For example $N = \sum_{ijk} n_{ijk} A_{ijk}$.

[21] This is a simplifying assumption that focuses the analytical analysis on the primary costs of the policies. Pre-existing distortionary taxation and a binding government budget are included in the numerical model.

3.2 Primary Costs of Alternative Policies

Emissions Tax

If emissions are observable, an emissions tax is available and achieves the first-best outcome.[22] Assume that each landowner is taxed at rate t_E for emissions generated by their production activities. The per-unit profit functions become $\pi_{ijk} = P_k y_{ijk} - n_{ijk} - m_{ijk} - l_{ijk} - t_E e_{ijk}$. The tax revenue from the policy, and therefore the transfer to the consumer, is $G = t_E E$.

The efficiency cost, excluding the benefits from emissions reductions, of a marginal increase in the emissions tax is:

$$-\frac{1}{\lambda_I}\frac{dV}{dt_E} = \underbrace{-t_E \sum_{ijk} e_{ijk}\frac{dA_{ijk}}{dt_E}}_{dW_A} + \underbrace{\sum_{ijk} A_{ijk}\left(P_k y^n_{ijk} - 1\right)\left(-\frac{dn_{ijk}}{dt_E}\right)}_{dW_N} + \underbrace{\sum_{ijk} A_{ijk}\left(P_k y^m_{ijk} - 1\right)\left(-\frac{dm_{ijk}}{dt_E}\right)}_{dW_M} \quad (8)$$

where λ_I is the marginal utility of income, $y^n_{ijk} = \frac{\partial y_{ijk}}{\partial n_{ijk}}$ and $y^m_{ijk} = \frac{\partial y_{ijk}}{\partial m_{ijk}}$. The first term, dW_A, is the *land allocation effect*, which is the efficiency cost of landowners shifting land away from emissions intensive crops. This effect equals the sum across all parcels and crops of the change in the land allocation times the change in per-unit profit due to the emissions tax. The final two terms, dW_N and dW_M, are the polluting and mitigating *input effects*. The input effects are the costs, due to lost profits to the land endowment, resulting from reduced use of the polluting input and increased use of the mitigating input.

The emissions tax is efficient because the cost of the policy is distributed across all three channels of adjustment. Second-best policies are unable to fully utilize all of the channels to reduce emissions, and are therefore more costly.

Uniform Input Tax

Consider a tax on the polluting input of t_N, but note that a tax/subsidy on the mitigating input would lead to analogous channels of adjustment. The per-unit profit functions are $\pi_{ijk} = P_k y_{ijk} - (1 + t_N)\, n_{ijk} - m_{ijk} - l_{ijk}$ and tax revenue is $G = t_N N$. The efficiency costs of a marginal increase in the input tax is:

$$-\frac{1}{\lambda_I}\frac{dV}{dt_N} = \underbrace{-t_N \sum_{ijk} n_{ijk}\frac{dA_{ijk}}{dt_N}}_{dW_A} + \underbrace{\sum_{ijk} A_{ijk}\left(P_k y^n_{ijk} - 1\right)\left(-\frac{dn_{ijk}}{dt_N}\right)}_{dW_N}. \quad (9)$$

[22] As illustrated in the appendix, comparing the first-order conditions of the competitive equilibrium problem to those of the social planner's problem proves that an emissions tax equal to the marginal damage of emissions is socially optimal.

The uniform input tax exploits only a single input effect and partially exploits the land allocation effect. The input tax only causes landowners to reduce the use of the polluting input, but does not induce additional use of the mitigating input. The land allocation effect is only partially utilized because the change in crops' per-unit profit depends on the use of the polluting input rather than the contribution to emissions.

Acreage Tax

Since the land allocation is observable, a tax on the land allocated to a heavily polluting crop, indexed h, may be reasonably easy to implement. The per-unit profits of crop h are $\pi_{ijh} = P_h y_{ijh} - n_{ijh} - m_{ijh} - l_{ijh} - t_h$, and government payments are: $G = \sum_{ij} A_{ijh} t_h$. The efficiency costs of a marginal increase in an acreage tax is:

$$-\frac{1}{\lambda_I}\frac{dV}{dt_h} = \underbrace{-\sum_{ij}\left(\pi_{ijh} - L_{ij}^h - \lambda_{ij}\right)\frac{dA_{ijh}}{dt_h}}_{dW_A} \tag{10}$$

where λ_{ij} is the multiplier on the land constraint in parcel ij and L_{ij}^h are the marginal management costs with respect to land in crop h. The efficiency cost is the sum across all parcels of the change in profit from shifting a unit of land away from the heavily polluting crop into an alternative crop times the change in the land allocated to the heavily polluting crop.[23] The acreage tax only partially utilizes the land allocation effect because the tax does not alter the per-unit profits of other polluting crops or account for the heterogeneity in emissions for the taxed crop across parcels.

The analytical model illustrates the channels through which single, uniform policy instruments lead to primary costs. However, insights can be gleaned about more complicated policy configurations. A non-uniform input tax that varies by some combination of region, parcel or crop will improve on the uniform input tax if the input tax rates can be set in a manner that accounts for heterogeneity in marginal emissions rates across groups. Likewise, pairing a set of acreage taxes with an input tax could more fully utilize the land allocation effect. The costs of non-uniform policies and combinations of policies are explored further using the numerical model.

4 Numerical Framework

The numerical model is a national-scale integrated biophysical and general equilibrium framework that accounts for agricultural production decisions at the county level. Changes in farm-level behavior impact world and national prices, consumer decisions and trade. The model is calibrated to baseline economic and

[23] For any of the untaxed crops the first-order condition is $\pi_{ijk} - L_{ij}^k = \lambda_{ij}$, so λ_{ij} represents the profit obtained from shifting a unit of land into the production of an untaxed crop.

agricultural data and output from biophysical model simulations.

The numerical model takes broadly the same structure as the analytical model, with three major additions. First, to account for exports of US crops the numerical model includes two "countries" with open economies, the US and the rest-of-world (ROW). ROW is an aggregate of all countries excluding the US. Both countries are endowed with labor and land, which are immobile across countries. The countries trade crops and intermediate goods. Since the focus is on the implications of US policies, the model is more detailed for the US than the ROW. Second, a number intermediate sectors are added to better represent the relationship between farm level decisions that affect crop supply and national-level outcomes. Finally, the numerical model allows for an endogenous labor supply, and the government funds a fixed real transfer to the consumer using a labor tax. This final set of additions allows the model to capture interactions between the environmental policies and the fiscal system.[24]

The functional forms and assumptions for U, y_{ijk}, e_{ijk}, L_{ij} and intermediate production are laid out in the following sections. When necessary, the superscript $r \in \{\mathrm{US}, \mathrm{ROW}\}$ is used to denote goods or activities in a specific country. For clarity of notation, the superscript is dropped from the functional forms described below. Unless otherwise noted, arguments and parameters of each function are country specific.

4.1 US Demand

In the numerical model, the representative consumer in the US demands a composite consumption good F produced primarily with crops, which will be referred to as food, rather than consuming each of the crops directly. Utility is a set of nested constant-elasticity-of-substitution (CES) functions:

$$U = \left(\alpha_U CF^{\rho_U} + (1-\alpha_U)\left(\bar{L} - L\right)^{\rho_U}\right)^{\frac{1}{\rho_U}}$$
$$CF = \left(\alpha_{CF}(F - \bar{F})^{\rho_{CF}} + (1-\alpha_{CF})\, C^{\rho_{CF}}\right)^{\frac{1}{\rho_{CF}}} \tag{11}$$

where ρ_U and ρ_{CF} are functions of the chosen elasticities of substitution, σ_U and $\sigma_C F$, according to $\rho = \frac{\sigma - 1}{\sigma}$, the α terms are calibrated share parameters. This utility specification follows closely from Parry (1999). The upper nest accounts for the tradeoff between aggregate consumption CF while the lower level nest accounts for the tradeoff between consumption of food and all other consumption. A key feature of this framework is the inclusion of $\bar{F}$ in the lower level nest. This is a calibrated parameter that allows the expenditure elasticities for F and C to differ and, if $\bar{A}$ is positive, for C to be a closer substitute for leisure than food.[25]

[24] Note, mitigating agricultural inputs have yet to be incorporated into the numerical model.

[25] If $CF(\cdot)$ took the standard CES form, the expenditure elasticities for F and C would both be 1. Therefore any change in CF would lead to proportional increases in both goods and the demand elasticities for F and C with respect to the wage rate would be the same.

4.2 US Agricultural Production

The model captures differences in crop yields and emissions rates at county level. Accounting for heterogeneity in yields and emissions rates requires solving for county-crop specific N application rates. As a consequence, simplifications are made in other areas of the model to maintain feasibility. Most significantly, mitigation policies are assumed to only impact the type of crops grown on irrigated land but not the fraction of irrigated land in a county. It is therefore possible to treat irrigated land and rainfed land in a given county as two separate parcels. For example, in the baseline data, Jefferson county Nebraska has 0.056 million hectares of rainfed cropland, and 0.035 million hectares of irrigated cropland. Jefferson county is treated as two parcels, one with 0.056 million hectares of rainfed cropland and the other with 0.035 million hectares of irrigated cropland. Therefore, in the numerical model, I represents states and J represent county-irrigation pairs. Since not all crops are grown in each region, the crop choice set is indexed by region, K_i.

Yield and Emissions Functions

Yield $y_{ijk}\left(n_{ijk}\right)$ and emissions $e_{ijk}\left(n_{ijk}\right)$ per unit land are quadratic functions of N application rates with crop-parcel specific parameters estimated from Daycent model output. The parameters of the yield function are restricted to impose strict concavity.[26] The emissions functions represent the sum of direct and indirect N_2O emissions and are assumed to be increasing and weakly convex.

Land Allocation

The unobservable management costs in equation (6) take the form:

$$L_{ij}\left(A_{ij1},\ldots,A_{ijK}\right)=\bar{A}_{ij}\frac{1}{\alpha_i^A}\left(l_{ij}+\sum_k \xi_{ijk}S_{ijk}+\sum_k S_{ijk}\log S_{ijk}\right) \tag{12}$$

where S_{ijk} is the share of parcel ij allocated to crop k and α_i^A, ξ_{ijk} and l_{ij} are calibrated parameters. Given this specification of management costs, the optimal land allocations in each parcel take simple logit forms:

$$A_{ijl}\left(\pi_{ij1},\ldots,\pi_{ijK}\right)=\bar{A}_{ij}\frac{\exp\left(\alpha_i^A\pi_{ijl}-\xi_{ijl}\right)}{\sum_k \exp\left(\alpha_i^A\pi_{ijk}-\xi_{ijk}\right)}. \tag{13}$$

The multinomial logit is a limited formulation because it forces an increase in returns for any crop to cause the same percentage reduction in all other crops. However, this limitation is partially justified due to the computational benefits of a closed form solution for the land allocation.

[26]The yield functions are given by $y_{ijk}=\beta^0_{ijk}+\beta^1_{ijk}n_{ijk}+\beta^2_{ijk}n^2_{ijk}$, with $\beta^1_{ijk}>0$ and $\beta^2_{ijk}<0$.

4.3 ROW Demand

The representative consumer in the ROW derives utility from consumption goods C and F and land held out of agricultural production:

$$U = \left(\alpha_U C^{\rho_U} + (1-\alpha_U) F^{\rho_U}\right)^{\frac{1}{\rho_U}} + \frac{{A_U}^{1+\frac{1}{\eta_{A_U}}}}{\gamma_{A_U}(1+\eta_{A_U})} \tag{14}$$

where $A_U = \left(\bar{A} - A_{AG}\right)$ and A_{AG} is the amount of land available for agriculture. Allowing land to enter the additively separable component of utility is a simple means for endogenizing the supply of land for agriculture. ROW income is the sum of returns to the labor and land endowments.

4.4 Final and Intermediate Production

Intermediate goods and the final consumption goods, F and C, are produced by profit maximizing firms with CES technology of the form:

$$X_s^r = \gamma_s^r \left(\sum_q \alpha_{sq}^r {X_{sq}^r}^{\rho_s^r}\right)^{\frac{1}{\rho_s^r}} \tag{15}$$

where X_s^r is the production of good s and X_{sq}^r is quantity of good q used in the production of good s in country r, and $\rho_s^r = \frac{\sigma_{sq}^r - 1}{\sigma_{sq}^r}$. σ_{sq}^r, γ_s^r and α_{sq}^r are calibrated parameters. s indexes the set of all intermediate and final goods, while q indexes the set of all primary factors, intermediate goods and final goods. Since the technology exhibits constant returns to scale, profit in all intermediate industries will be zero. Table 1 displays the specific structure of intermediate production, including the goods produced in each country and the inputs used in the production of each good.[27]

N is produced from labor in the US with a linear production function: $N = \gamma_N L$. Therefore $P_N = \frac{P_L}{\gamma_N}$.

4.5 Market Clearing and Trade

Aggregate demand must equal aggregate supply at the country level for each non-traded good, and at the world level for each traded good. Trade is assumed to balanced.

4.6 Solution Method

Given a set of environmental policy variables, equilibrium is computed by searching for a vector of activity levels, constraint multipliers and prices that solve the first-order conditions for optimal consumption and

[27] Note, aggregate ROW agricultural production is included as an intermediate good because it is produced from land and labor with CES technology.

production, market clearing conditions, and zero-profit conditions.[28]

The model must be solved as a complementarity problem to account for non-negativity constraints on N application rates.[29] The application rate for crop-parcel ijk must satisfy the complementarity condition:

$$0 \leq -\left(P_k \frac{\partial y_{ijk}}{\partial n_{ijk}} - (P_N + \tau_N) - \tau_E \frac{\partial e_{ijk}}{\partial n_{ijk}}\right) \quad \perp \quad 0 \leq n_{ijk} \tag{16}$$

where $\perp$ indicates that if either condition is non-binding, the other condition must be satisfied with equality.[30] Formally, denote Ω as the vector of choice variables in the equilibrium search and Φ as the vector of environmental policy variables. Let $0 \leq \text{EQM}(\Omega; \Phi)$ be the vector of equilibrium conditions. Given policy values, equilibrium is solved by searching for Ω that satisfies:[31]

$$0 \leq \text{EQM}(\Omega; \Phi) \perp 0 \leq \Omega. \tag{17}$$

Optimal Policy Problem

An MPEC formulation is used to compute the optimal policy variables that achieve a target level of emissions, $\bar{E}$. Denote equilibrium emissions as $E(\Omega; \Phi)$ and welfare of country r as $U^r(\Omega; \Phi)$ and let θ^r be utility weights. The optimal policy variables are those that maximize the weighted sum of each country's welfare subject to the emissions constraint, while all other variables satisfy the equilibrium conditions:

$$\begin{aligned} &\max_{\Omega, \Phi} \sum_r \theta^r U^r(\Omega; \Phi) \\ &\text{subject to:} \\ &0 \leq \text{EQM}(\Omega; \Phi) \perp 0 \leq \Omega \\ &E(\Omega; \Phi) \leq \bar{E}. \end{aligned} \tag{18}$$

[28] Activity levels are final consumption quantities, production quantities and inputs used for all final and intermediate goods and N application rates. Given prices and input levels, there is a closed form solution for the land allocation, so these variables do not enter the equilibrium search. Constraint multipliers include the multiplier associated with each country's income constraint and the multipliers associated with each production constraint. Prices are the domestic prices of all non-traded goods and the world prices of traded goods. The zero-profit conditions apply to all final and intermediate goods, excluding crops, and establish the prices of these goods.

[29] If, given the yield functions, emissions functions and policies, closed form solutions can be derived for the optimal n_{ijk}, then n_{ijk} can be removed as a choice variables in the agricultural problem, and the per-unit land profit functions can be written as functions of prices and policies.

[30] Equation (16) is a compact representation of the Karush-Kuhn-Tucker conditions for maximization with non-negativity constraints: $-\left(P_k \frac{\partial y_{ijk}}{\partial n_{ijk}} - (P_N + \tau_N) - \tau_E \frac{\partial e_{ijk}}{\partial n_{ijk}}\right) \geq 0$, $n_{ijk} \geq 0$ and the complementary slackness condition $n_{ijk}\left(P_k \frac{\partial y_{ijk}}{\partial n_{ijk}} - (P_N + \tau_N) - \tau_E \frac{\partial e_{ijk}}{\partial n_{ijk}}\right) = 0$. Using $\perp$ removes the need to report the complementary slackness condition and is consistent with how the problem must be structured for use with numerical complementarity solvers.

[31] The complementarity conditions are only necessary for the N application rates and the associated first-order conditions. All other variables are non-negative in equilibrium, so the associated equilibrium conditions will hold with equality.

The multiplier associated with the emissions constraint represents the utility cost of a marginal change in emissions.

5 Data and Calibration

5.1 Baseline Data

Production and Consumption

Table 1 summarizes the baseline production and consumption data set. The US portion of this data set was mainly derived from the 2007 Bureau of Economic Analysis NIPA Input-Output tables (BEA, 2015) and the USDA's Foreign Agricultural Service Production, Supply and Distribution (PSD) data (FAS, 2015). Data for the ROW was derived largely from World Bank (2015) and FAO (2015) statistics. The first column in each panel reports baseline values of the endowments and crops supplied by each country.[32] The value of seven crops (corn, soybean, wheat, cotton, sorghum, legume hay and grass hay) is calculated using baseline yields, land allocation and crop prices described below. The remaining columns report the value of goods consumed in the production of intermediate goods and by representative consumers. The final column in the ROW panel reports the value of imports to ROW from the US.

In the US, the intermediate goods are meant to broadly reflect the flow of agricultural products from production to end use. The intermediate goods included are hay (HAY), processed soybeans (SB), ethanol (ETOH), meat (MEAT) food (F) and an aggregate consumption good (C). These categories reflect the primary intermediate and final end uses for crops based on USDA data. HAY is an aggregate of all grass hay and alfalfa, and is used solely for the production of meat. Processed soybeans is a combination of soybeans and labor that represents soybean meal and soybean oil. Processed soybeans can be used domestically to produce food or meat or can be exported. Ethanol represents industrial uses of corn, which is predominantly the production of ethanol for transportation fuel, and is used to produce the aggregate consumption good. MEAT represents animal agriculture and F represents the final food good purchased by consumers. In the ROW, only broad aggregate goods are considered, including the aggregates of imported US agricultural products (AG, US) and ROW agricultural products (AG, ROW) and all agricultural products (AG). This simple structure allows for the ROW supply and demand of agricultural products, and in turn ROW demand for US crops, to respond to US environmental policies. See appendix section A.2.1 for details regarding the construction of the baseline production and consumption data set.

[32] Since A in the US is used solely by the agricultural sector it is not reported in this table.

Agriculture

The agricultural model is calibrated to a detailed agricultural data set constructed primarily from USDA sources including the National Agricultural Statistics Service's (NASS) annual surveys and Census of Agriculture (NASS, 2014b) and the Economic Research Service's (ERS) Agricultural Resource Management Survey (ARMS) data (ERS, 2014a) and Commodity Costs and Returns (ERS, 2014b). Since the model captures long run equilibrium adjustments, the agricultural data used in the model is the average of the available annual data reported in the USDA sources for the years 2003 to 2012.

The model represents the production of seven crops: corn, soybean, wheat, cotton, sorghum, legume hay and grass hay.[33] These seven crops comprise the majority of US crop production, accounting for roughly 90% of land allocated to field crops, and 87% of the value of crop production in 2002, 2007 and 2012 (NASS, 2014b). Only the most significant crop variety in terms of land shares and quantities is modeled. Therefore, cotton represents upland cotton and wheat represents winter wheat.

Production decisions are modeled in 1,968 counties across 35 states. Counties are included based on the quantity of land allocated to the seven modeled crops. The included counties, mapped in Figure A.1, account for more than 95% of total land allocated to the seven modeled crops in each year between 2002 and 2012. Irrigated agriculture is modeled when a significant ($> 5\%$) share of total land in a county is irrigated. A map of irrigated and rainfed counties is provided in Figure A.2. In total, 2,572 county-irrigation combinations are included in the model, with 1,329 counties containing only rainfed cropland, 604 counties containing both rainfed and irrigated cropland and 35 counties containing only irrigated cropland. Crop shares by county and irrigation status were calculated from harvested acreage data from the Census of Agriculture reported by NASS (2014b). The average of the 2007 and 2012 census data was used to calculate these shares. Irrigation data is from the Farm and Ranch Irrigation Survey supplement to the Census of Agriculture. See section A.2.2 for additional information about the selection of counties and the construction of crop shares.

County level yields for rainfed and irrigated crop production, state level N fertilizer application rates, and productions costs for farm production regions are also collected for use in calibration from the Census of Agriculture, ARMS and Commodity Costs and Returns data, respectively.

5.2 Parameters

US Utility

The US utility functions, equation (11), are calibrated to match key elasticities of demand and replicate baseline quantities. First, σ_U and the ratio of the value of leisure to the total value of consumption are set

[33] Corn and sorghum are harvested for grain. Legume hay is represented by alfalfa.

so that the compensated labor supply elasticity is 0.4 and the compensated elasticity of labor supply is 0.15. These values are consistent with similar studies (Parry, 1999; Goulder et al., 1999; Bovenberg et al., 2008), although a recent review suggests that aggregate labor supply elasticities may have fallen in recent years (McClelland and Mok, 2012). Then $\bar{F}$ is chosen so that the expenditure elasticity for F is 0.4 and σ_{CF} is chosen so that the uncompensated demand elasticity for F is -0.35. These values are consistent both with previous studies focusing on agricultural policies (Parry, 1999) and empirical estimates (Muhammad et al., 2011).[34]

US Intermediate Production

Grass hay and alfalfa are assumed to close substitutes in the production of the hay aggregate ($\sigma = 1.5$). The elasticities of substitution for ethanol production and soybean processing are set close to zero ($\sigma = 0.05$), so that labor is nearly a perfect compliment to the crop input in both sectors. The elasticities of substitution for C, MEAT and F production are set to 0.5.

Yield and Emissions Functions

The yield and emissions function parameters are estimated from output of the Daycent biogeochemical model (Parton et al., 1998) used in the EPA's GHG Inventory (US EPA, 2014) to estimate GHG emissions from agricultural soils. Daycent is a widely used and highly cited process model that simulates carbon, nitrogen, phosphorous and sulfur dynamics for agroecosystems on a daily timestep based on site specific characteristics for soil and weather. Critically, Daycent is able to simulate the carbon in grain and straw yields, the N_2O emissions resulting from N available from synthetic fertilizers, livestock manure, crop residues and the mineralization of soil organic matter and asymbiotic fixation, and N volatilization and leaching. The model is capable of simulating a wide range of crop patterns and numerous management practices, including fertilization rates, irrigation status and tillage practice.

To generate a dataset from which the yield and emissions functions can be estimated, Daycent simulations were conducted for a large sample of agricultural sites across the US. The simulations are based on site-specific soil attributes and daily weather and the outputs represents average yield and N_2O emissions over a 30 year period after a management change. Linear mixed effects models are used to estimate the relationship between yields and emissions, and crop and management choices from the Daycent model outputs. The explanatory variables in the regression models include N applied and N applied squared, organic amendments and organic amendments squared, the crop residue removal rate, dummy variables for crop, tillage, irrigation status and

[34] Parry (1999) uses -0.4 for the uncompensated demand elasticity for agricultural products, and 0.4 for the income elasticity of agricultural products. (Muhammad et al., 2011) suggest values closer to 0.35 and -0.3 for the income and uncompensated demand elasticities for food, respectively.

fertilizer timing and site specific average temperature, a soil moisture index and soil sand fraction as well as first order interactions between all variables. Separate models were estimated for broad regions defined in Table A.1. Yield and emissions as functions of N applied are obtained for each county, irrigation status and crop combination, ijk, by evaluating the models for all other variables. County level heterogeneity arises from state level average temperature and county level data for the moisture index.

An adjusted set of yield functions are derived from the estimated yield functions for use in the economic model. The yield functions that enter the economic model are calibrated so that, given baseline prices, the yield and N input rate predictions of the economic model match baseline economic data at the regional level, while Daycent output drives the heterogeneity in yields and optimal N application rates at the parcel level. Additional details are provided in section A.3.

Land Management Costs

Parameters α_i^A in the land management cost function are assumed to be uniform and are calibrated so that in the baseline the corn area elasticity with respect to the corn price is 0.35, which is between the short and long run estimates of (Hendricks et al., 2014) and is consistent with more dated evidence (Lin et al., 2000). The remaining own price elasticities for the remaining crops lie between 0.16 (wheat) and 0.38 (sorghum). Given values of α_i^A, parameters ξ_{ijk} are set so that predicted land shares match observed land shares. Finally, l_{ij} are set so that total management costs for each parcel are zero at the baseline land allocation.

ROW Utility

σ_U^{ROW} is calibrated so the uncompensated elasticity of demand for F is -0.45. This value is chosen so that the elasticity of demand for F is slightly more elastic in the ROW than the US, consistent with the findings of Muhammad et al. (2011).[35]

ROW Production

The elasticity of land supply is calibrated to 0.1, which is consistent with empirical estimates from Barr et al. (2011). A low elasticity value is chosen here because ROW agricultural production represents all agricultural activities, so the extensive margin will not account for shifts between agricultural uses, such as between cropland and pasture. The elasticity of substitution between A and L in the production of ROW agricultural products, $\sigma_{AG_{ROW}}$, is set to 0.05 so that the elasticity of output per unit land with respect to the price of agricultural products is small (Berry and Schlenker, 2011; Scott, 2013).

[35] A standard CES utility function is used for the ROW because evidence suggests that the income elasticity of food consumption is closer to 1 outside the US (Muhammad et al., 2011).

The elasticity of substitution for the ROW agricultural aggregate and the elasticity of substitution for US agricultural products are calibrated so the aggregate ROW demand for US crops is -0.4 and the ROW demand elasticity for corn imports is -0.6. The remaining elasticities of demand for crop imports range from -0.53 to -0.66. These elasticities of export demand are roughly in line with Gardiner and Dixit (1987).

The elasticity of substitution for the ROW agricultural consumption good is set so that labor is nearly a perfect compliment to agricultural products ($\sigma = 0.05$).

6 Preliminary Results

The numerical model is used to evaluate the welfare implications of reducing agricultural N_2O emissions for an emissions tax, and a range of policy options based on easily observable quantities. In addition to a tax on emissions and a uniform N tax, a non-uniform N tax that varies by region (tN_i) along with combinations of the N taxes and crop-specific acreage taxes, both uniform ($tN + tA_k$,$tN_i + tA_k$) and non-uniform across regions ($tN + tA_{ik}$ and $tN_i + tA_{ik}$) are considered.[36] Costs are simulated for a series of decreasing total emissions targets, up to a 5% overall reduction in agricultural N_2O.

The first step in the analysis is to obtain the values of the taxes that minimize the primary costs of achieving the series emissions targets by solving the problem in equation (18). To recover optimal policy values that account only for the environmental motivation, θ^r are set to one for each country, t_L is set to zero and all government revenue to be returned to the consumer as a lump sum transfer. These modifications prevent the environmental policies from being set for terms of trade or revenue raising purposes or to alleviate a pre-existing distortion.

Marginal Primary Costs

The marginal primary costs of emissions reductions for each policy are plotted in Figure 1 and presented in tabular form, along with the ratio of primary costs to the primary costs of the emissions tax, in Table 2. To aid with interpretation, the average N application rate for all US cropland and the N_2O conversion factor, the percent of N applied that is converted to N in N_2O, are also reported in Table 2. The simulation results suggest that even with first-best policies, only small cuts in N_2O are achievable at reasonable costs. With the unavailable tax on N_2O, a 2.5% reduction in emissions can be achieved at marginal costs of just over 60 $/t$CO_2$e. The costs of second-best policies are markedly higher, but can approach first-best.

The uniform tax on N is the most costly policy considered and is not close to Pigouvian. At a 2.5%

[36] The costs of the two sets of acreage taxes are also simulated independently, but these policies from the results presented below because the marginal primary costs are considerably higher than any of the other policies.

reduction in emissions, the marginal costs of this instrument are nearly 40% higher than the emissions tax. The additional costs are incurred because the tax on N cannot account for differences in emissions rates across crops or parcels. As a result, the uniform tax on N induces too drastic a reduction in N use and too small a reduction in the N_2O conversion rate, relative to the tax on emissions.

Allowing the N tax to vary across regions drastically reduces primary costs. The non-uniform N tax achieves a 2.5% reduction at marginal costs only 10% higher than the emissions tax, but more than 20% percent lower than the uniform N tax. The non-uniform N tax is able to exploit regional differences in marginal yield and N_2O rates, so the land allocation and input use effects more closely resemble those of the emissions tax. As a result, the reduction in N use is not nearly as drastic as with the uniform N tax. However, heterogeneity in emissions rates and yields within broader regions prevent the non-uniform N tax from achieving the first-best. That the non-uniform tax on N reduces emissions with costs approaching the first-best policy indicates that the majority of the heterogeneity in yield and emission rates occurs at a fairly broad spatial scale.

Regionally differentiated policies could create incentives for evasion by transporting taxed goods across borders. However, only 10 broad regions are considered in this analysis, so transporting fertilizer from outside a region is unlikely to be cost effective for a vast majority of parcels.

Pairing N taxes with crop-specific acreage taxes is another strategy that will lower marginal costs relative to N taxes alone. N taxes alter the land allocation based on N application rates, rather than emissions rates. When paired with an N tax the acreage taxes will, to a limited extent, correct the allocation of land by altering the relative returns to crops. However, the reductions in costs due to the inclusion of acreage taxes are small. For a 2.5% reduction in emissions, pairing crop-specific acreage taxes with a uniform N tax lowers marginal costs by only 3% relative to the uniform N tax alone. Pairing crop-specific acreage taxes with a non-uniform N tax leads to cost reductions of a similar magnitude. Allowing the acreage taxes to vary by region lowers costs further but only by a small amount, less than 1% relative to the crop-specific acreage taxes.

Although the cost reductions that come with pairing acreage taxes are small, the marginal costs of a non-uniform N tax and acreage taxes are nearly as low as the unavailable emissions tax. The combinations of the non-uniform N tax with uniform and regionally varying acreage taxes are only 5% and 6% more expensive than the unavailable emissions tax. This illustrates that a well designed policy that regulates easily observable quantities can reduce N_2O emissions at costs only slightly higher than the first-best policy.

Marginal primary costs increase at an increasing rate for larger cuts in emissions. The rate of increase is similar for all policies. For a doubling in emission reductions from 2.5% to 5%, the marginal cost of the emissions tax increased by a factor of 2.16. As illustrated by the roughly constant primary cost ratios, the marginal costs of the second-best policies increase at nearly the same rate as the marginal costs of the emissions tax. For example, for the same doubling of emission reductions, the marginal costs of the uniform N tax increases by a factor of 2.21.[37]

Optimal Emission Reductions

The optimal level of emissions reductions for a given marginal social cost of CO_2 can be determined from Figure 1 by finding the level of emissions reductions that equates a given marginal social cost of CO_2 and marginal primary costs. These optimal levels of emissions reductions for each policy under three estimates for the social cost of CO_2 (Interagency Working Group on Social Cost of Carbon, 2013) are reported in Table 3.[38] At a social cost of carbon of 50 \$/tCO_2, it would be optimal to reduce N_2O emissions by 2% if the emissions tax were available. Optimal emissions reductions would only be 1.5% for a uniform N tax. But, optimal emissions reductions are 1.9% for the differentiated N tax and nearly 2% for the combinations of a differentiated N tax and crop specific acreage taxes.

Impacts on Agricultural Sector

Figure 4 allows for a comparison of alternative policies along a number of key dimensions that affect welfare of the agricultural sector in addition to primary costs. The first row in each panel reports total costs of achieving the targeted reduction in emissions, in terms of negative equivalent variation (EV). The second row reports total costs as a ratio of the total costs of the emissions tax. Overall, the trends in total costs follow very closely the trends in marginal costs discussed above.

The next four rows report changes in agricultural profit and agricultural tax payments due to each policy, both on a per hectare basis, and as a ratio of the emissions tax outcome. For a 2.5% reduction in emissions, the emissions tax causes a modest, 28 \$/ha, reduction in agricultural profit. This reduction in profit is smaller than the increase in agricultural taxes, 44 \$/ha, because reductions in supply due to shifts in land and N use due to the policy elevate crop prices. The final row in each panel reports the sum of the change in profit and tax payments, which quantifies the change in profits due to changes in crop prices.

Even though the alternative policies result in costs similar to the emissions tax, there are considerable differences in the impacts on profits of the agricultural sector. The impact of the uniform and non-uniform N taxes on profits are only 14% and 20% of the impacts of the emissions tax, respectively. The smaller impacts

[37]Note, the N_2O conversion ratio increases with larger emissions reductions because marginal emissions, the change in N_2O due to a change in N, is less than one on average. Reducing N_2O by scaling back N applications will therefore cause the N_2O conversion ratio to increase.

[38]The social costs of carbon used here are based on US government estimates for the social cost of carbon to be used in regulatory impact analyses (Interagency Working Group on Social Cost of Carbon, 2013). These values range from 11 to 90 \$/tCO_2 for 2010 The 30 and 50 \$/tCO_2 values used in 3 correspond to the estimates using 3% and 2.5% discount rates respectively. The 90 \$/tCO_2 estimate is meant to represent larger than expected impacts of climate change.

on profit for the N taxes are due primarily to lower tax payments, which are about 40% of the emissions tax payments. Change in profits do to elevated crop prices are much more similar. The large differences in tax payments for the emissions and N tax follows a theoretical result by Stevens (1988), who shows that for the same reduction in emissions the ratio of taxes collected by an input tax and emissions tax will be below one if the emissions function exhibits decreasing returns to scale, and above one if the emissions function exhibits increasing returns to scale.[39] The aggregate emissions function, as a function of only N application rates, exhibits returns of to scale of 0.4-0.33 depending on the level of emissions reductions, so the ratio of tax revenues will be well below one.[40]

Unlike the N taxes alone, the combinations of N taxes and acreage taxes have a larger impact on farmer profit than the emissions tax. This is because these policies induce larger tax payments than the emissions tax. For combinations of policies, the land allocation and N application rates are both inputs to the aggregate emissions function, and the emissions function exhibits increasing returns to scale.[41] Even more striking is the difference in farmer profit between N taxes alone and N taxes paired with acreage taxes. Pairing the uniform N tax with either set of acreage taxes causes the reduction in profits to jump from just under 4 $/ha to over 30 $/ha. Similar results occur when pairing the non-uniform N tax with either set of acreage taxes, although the impact on profits is not as large. These results raise questions about second-best combinations of policies if the welfare of the regulated sector is a concern. The small efficiency gains due to pairing acreage taxes with a N tax leads to substantial increases in tax payments and reductions in farmer profit.

7 Conclusion

This paper analyzes the primary costs of reducing N_2O emissions from the agricultural sector using an integrated biophysical and economic framework. Preliminary simulations suggest that an emissions tax can reduce emissions by 2.5% at a marginal cost of about 60 $/t$CO_2$e. A uniform N tax is substantially, 40% more expensive than the emissions tax. The most promising alternative policy is a non-uniform N tax that varies by region. Using this instrument emissions reductions are only 10% more costly than the emissions tax and has a much smaller impact on farm profit. Pairing input taxes with crop acreage taxes can slightly lower costs, but at the expense of large reductions in farmer profit.

The marginal cost estimates presented here are high relative to previous studies (McCarl and Schneider,

[39] Specifically, Stevens (1988) shows that, if the emissions function is homogeneous, the ratio of tax revenues will equal the degree of homogeneity of the emissions function.

[40] The relevant emissions function for the N taxes is $E(\boldsymbol{n}_{ij}) = \sum_{ijk} A_{ijk}(\boldsymbol{n}_{ij}) e_{ijk}(n_{ijk})$, where $A_{ijk}(n_{ijk})$ is the land allocation resulting from the choice of N rates. Local approximations of the returns to scale for this function are obtained by calculating the change in emissions due to a 1% increasing all N application rates, while allowing the land allocation to adjust.

[41] In this case, $E(\boldsymbol{n}_{ij}, \boldsymbol{A}_{ij}) = \sum_{ijk} A_{ijk} e_{ijk}(n_{ijk})$. If $\boldsymbol{n}_{ij}$ is fixed, E exhibits constant returns to scale. Therefore when both $\boldsymbol{n}_{ij}$ and $\boldsymbol{A}_{ij}$ are treated as inputs returns to scale must be greater than one.

2001; Garnache et al., 2014). However, these cost estimates are likely to be lower when mitigating inputs are included in the numerical model. Further, these costs are heavily dependent on key parameter assumptions, such as the crop area elasticities and the elasticity of food demand. A methodical sensitivity analysis of these parameter assumptions to identify the range of potential costs is a crucial next step.

References

Antle, J., S. Capalbo, S. Mooney, E. Elliott, and K. Paustian (2003). Spatial Heterogeneity, Contract Design, and the Efficiency of Carbon Sequestration Policies for Agriculture. *Journal of Environmental Economics and Management 46*(2), 231–250.

Antle, J. M., S. M. Capalbo, K. Paustian, and M. K. Ali (2007). Estimating the Economic Potential for Agricultural Soil Carbon Sequestration in the Central United States Using an Aggregate Econometric-Process Simulation Model. *Climatic Change 80*(1-2), 145–171.

Balasubramanian, V., B. Alves, M. Aulakh, M. Bekunda, Z. Cai, L. Drinkwater, D. Mugendi, C. van Kessel, and O. Oenema (2004). Crop, Environmental, and Management Factors Affecting Nitrogen Use Efficiency. In A. Mosier, J. K. Syers, and J. R. Freney (Eds.), *Agriculture and the Nitrogen Cycle: Assessing the Impacts of Fertilizer Use on Food Production and the Environment*. Washington DC: Island Press.

Barr, K. J., B. A. Babcock, M. A. Carriquiry, A. M. Nassar, and L. Harfuch (2011). Agricultural Land Elasticities in the United States and Brazil. *Applied Economic Perspectives and Policy 33*(3), 449–462.

BEA (2015). US Department of Commerce, Bureau of Economic Analysis, Industry Data, Input-Output. `http://www.bea.gov/iTable/index_industry_io.cfm` (accessed March 14, 2015).

Berry, S. and W. Schlenker (2011). Technical Report for the ICCT: Empirical Evidence on Crop Yield Elasticities.

Bovenberg, A. L., L. H. Goulder, and M. R. Jacobsen (2008). Costs of Alternative Environmental Policy Instruments in the Presence of Industry Compensation Requirements. *Journal of Public Economics 92*(5-6), 1236–1253.

CARB (2014). First Update to the Climate Change Scoping Plan: Building on the Framework. Technical report, California Air Resources Board.

Cavigelli, M. A., S. J. D. Grosso, M. A. Liebig, C. S. Snyder, P. E. Fixen, R. T. Venterea, A. B. Leytem, J. E. McLain, and D. B. Watts (2012). US Agricultural Nitrous Oxide Emissions: Context, Status, and Trends. *Frontiers in Ecology and the Environment 10*(10), 537–546.

De Cara, S., M. Houz, and P.-A. Jayet (2005). Methane and Nitrous Oxide Emissions from Agriculture in the EU: A Spatial Assessment of Sources and Abatement Costs. *Environmental and Resource Economics 32*(4), 551–583.

De Cara, S. and P.-A. Jayet (2000). Emissions of Greenhouse Gases from Agriculture: the Heterogeneity of Abatement Costs in France. *European Review of Agricultural Economics 27*(3), 281–303.

Del Grosso, S. J., W. J. Parton, P. R. Adler, S. C. Davis, C. Keough, and E. Marx (2012). DAYCENT Model Simulations for Estimating Soil Carbon Dynamics and Greenhouse Gas Fluxes from Agricultural Production Systems. In M. Liebig, A. J. Franzluebbers, and R. Follet (Eds.), *Managing Agricultural Greenhouse Gases*, pp. 241–250. Elsevier.

Del Grosso, S. J., W. J. Parton, A. R. Mosier, M. K. Walsh, D. S. Ojima, and P. E. Thornton (2006). DAYCENT National-Scale Simulations of Nitrous Oxide Emissions from Cropped Soils in the United States. *Journal of Environmental Quality 35*(4), 1451–1460.

Eagle, A., L. Henry, L. Olander, K. Haugen-Kozyra, N. Millar, and G. Robertson (2012). Greenhouse Gas Mitigation Potential of Agricultural Land Management in the United States: A Synthesis of the Literature. Technical report, Nicholas Institute for Environmental Policy Solutions, Durham, NC.

EPA (2012). Global Anthropogenic Non-CO_2 Greenhouse Gas Emissions: 1990 - 2030. Technical Report EPA 430-R-12-006, Office of Atmospheric Programs, Climate Change Division, US EPA, Washington DC.

Erisman, J. W., M. A. Sutton, J. Galloway, Z. Klimont, and W. Winiwarter (2008). How a Century of Ammonia Synthesis Changed the World. *Nature Geoscience 1*(10), 636–639.

ERS (2014a). US Department of Agriculture, Economic Research Service, ARMS Farm Financial and Crop Production Practices. http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices.aspx (accessed September 8, 2014).

ERS (2014b). US Department of Agriculture, Economic Research Service, Commodity Costs and Returns. http://www.ers.usda.gov/data-products/commodity-costs-and-returns.aspx (accessed September 8, 2014).

FAO (2015). FAOSTAT. http://faostat3.fao.org/home/E (accessed May 8, 2015).

FAS (2015). US Department of Agriculture, Foreign Agricultural Service, Production, Supply and Distribution Online. http://apps.fas.usda.gov/psdonline/psdHome.aspx (accessed March 14, 2015).

Fullerton, D. and L. Gan (2005). Cost-Effective Policies to Reduce Vehicle Emissions. *The American Economic Review 95*(2), 300–304.

Fullerton, D. and S. West (2010). Tax and Subsidy Combinations for the Control of Car Pollution. *The B.E. Journal of Economic Analysis & Policy, Advances 10*(1).

Fullerton, D. and S. E. West (2002). Can Taxes on Cars and on Gasoline Mimic an Unavailable Tax on Emissions? *Journal of Environmental Economics and Management 43*(1), 135–157.

Gardiner, W. and P. M. Dixit (1987). *Price Elasticity of Export Demand: Concepts and Estimates*. US Department of Agriculture, Economic Research Service.

Garnache, C., P. Mérel, J. Lee, and J. Six (2014). The Social Costs of Second-Best Policies: Evidence from Agricultural GHG Mitigation. Working Paper.

Goulder, L. H., I. W. H. Parry, R. C. Williams III, and D. Burtraw (1999). The Cost-Effectiveness of Alternative Instruments for Environmental Protection in a Second-Best Setting. *Journal of Public Economics 72*(3), 329–360.

Green, J. and E. Sheshinski (1976). Direct Versus Indirect Remedies for Externalities. *Journal of Political Economy 84*(4), 797–808.

Griffin, R. C. and D. W. Bromley (1982). Agricultural Runoff as a Nonpoint Externality: A Theoretical Development. *American Journal of Agricultural Economics 64*(3), 547–552.

Helfand, G. E. and B. W. House (1995). Regulating Nonpoint Source Pollution Under Heterogeneous Conditions. *American Journal of Agricultural Economics 77*(4), 1024–1032.

Hendricks, N. P., A. Smith, and D. A. Sumner (2014). Crop Supply Dynamics and the Illusion of Partial Adjustment. *American Journal of Agricultural Economics 96*(5), 1469–1491.

Hensen, A., U. Skiba, and D. Famulari (2013, June). Low Cost and State of the Art Methods to Measure Nitrous Oxide Emissions. *Environmental Research Letters 8*(2).

Hoben, J. P., R. J. Gehl, N. Millar, P. R. Grace, and G. P. Robertson (2011). Nonlinear Nitrous Oxide (N_2O) Response to Nitrogen Fertilizer in On-Farm Corn Crops of the US Midwest. *Global Change Biology 17*(2), 1140–1152.

Horowitz, J. (2014). Greenhouse Gas Offsets: Analysis of Baseline Rules and Additionality for Reduced Nitrogen Application on Wheat. *Climate Change Economics 05*(02), 1450002.

Interagency Working Group on Social Cost of Carbon (2013). Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis-Under Executive Order 12866.

IPCC (1997). *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories*. Paris: OECD.

IPCC (2006). *2006 IPCC Guidelines for National Greenhouse Gas Inventories: Prepared by the National Greenhouse Gas Inventories Programme*. Hayama, Japan: Institute for Global Environmental Strategies. Eggleston H.S., Buendia L., Miwa K., Ngara T. and Tanabe K.(eds.).

IPCC (2014). *Climate Change 2014: Mitigation of Climate Change: Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press. Edenhofer, O. and Pichs-Madruga, R. and Sokona, Y. and Farahani, E. and Kadner, S. and Seyboth, K. and Adler, A. and Baum, I. and Brunner, S. and Eickemeier, P. (eds.).

Johnson, R. (2009). Climate Change: The Role of the US Agriculture sector. Technical Report RL33898, Congressional Research Service, Washington, DC.

Knittel, C. R. and R. Sandler (2013). The Welfare Impact of Indirect Pigouvian Taxation: Evidence from Transportation. Working paper, National Bureau of Economic Research.

Lin, W., P. C. Westcott, R. Skinner, S. Sanford, and D. G. De La Torre Ugarte (2000). Supply Response Under the 1996 Farm Act and Implications for the US Field Crops Sector. ERS Technical Bulletin No. 1888.

Marten, A. L., E. A. Kopits, C. W. Griffiths, S. C. Newbold, and A. Wolverton (2015). Incremental CH_4 and N_2O Mitigation Benefits Consistent with the US Government's SC-CO_2 Estimates. *Climate Policy 15*(2), 1–27.

McCarl, B. A. and U. A. Schneider (2001, December). Greenhouse Gas Mitigation in US Agriculture and Forestry. *Science 294*, 2481–2482.

McClelland, R. and S. Mok (2012). A Review of Recent Research on Labor Supply Elasticities. CBO Working Paper Series: 2012-12.

Mérel, P., F. Yi, J. Lee, and J. Six (2014). A Regional Bio-economic Model of Nitrogen Use in Cropping. *American Journal of Agricultural Economics 96*(1), 67–91.

Muhammad, A., J. L. Seale, B. Meade, and A. Regmi (2011). International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data. ERS Technical Bulletin Number 1929.

NASS (2014a). Published crop-specific data layer. `http://nassgeodata.gmu.edu/CropScape/` (accessed May 8, 2015).

NASS (2014b). US Department of Agriculture, National Agricultural Statistics Service, Quick Stats. `http://quickstats.nass.usda.gov/` (accessed September 8, 2014).

Ogle, S. M., B. A. McCarl, J. Baker, S. J. D. Grosso, P. R. Adler, K. Paustian, and W. J. Parton (2015). Managing the Nitrogen Cycle to Reduce Greenhouse Gas Emissions from Crop Production and Biofuel Expansion. *Mitigation and Adaptation Strategies for Global Change*, 1–16.

Parkin, T. B. (1987). Soil Microsites as a Source of Denitrification Variability. *Soil Science Society of America Journal 51*(5), 1194–1199.

Parkin, T. B. and T. C. Kaspar (2006). Nitrous Oxide Emissions from Corn-Soybean Systems in the Midwest. *Journal of Environmental Quality 35*(4), 1496–1506.

Parry, I. W. H. (1999). Agricultural Policies in the Presence of Distorting Taxes. *American Journal of Agricultural Economics 81*(1), 212–230.

Parton, W. J., M. Hartman, D. Ojima, and D. Schimel (1998). DAYCENT and its Land Surface Submodel: Description and Testing. *Global and Planetary Change 19*(1), 35–48.

Popp, A., H. Lotze-Campen, and B. Bodirsky (2010). Food Consumption, Diet Shifts and Associated Non-CO_2 Greenhouse Gases from Agricultural Production. *Global Environmental Change 20*(3), 451–462.

Powlson, D. S., T. M. Addiscott, N. Benjamin, K. G. Cassman, T. M. de Kok, H. van Grinsven, J.-L. L'hirondel, A. A. Avery, and C. Van Kessel (2008). When Does Nitrate Become a Risk for Humans? *Journal of Environmental Quality 37*(2), 291–295.

Powlson, D. S., C. M. Stirling, M. L. Jat, B. G. Gerard, C. A. Palm, P. A. Sanchez, and K. G. Cassman (2014). Limited Potential of No-till Agriculture for Climate Change Mitigation. *Nature Climate Change 4*(8), 678–683.

Ravishankara, A. R., J. S. Daniel, and R. W. Portmann (2009). Nitrous Oxide (N_2O): The Dominant Ozone-Depleting Substance Emitted in the 21st Century. *Science 326*(5949), 123–125.

Reay, D. S., E. A. Davidson, K. A. Smith, P. Smith, J. M. Melillo, F. Dentener, and P. J. Crutzen (2012). Global Agriculture and Nitrous Oxide Emissions. *Nature Climate Change 2*(6), 410–416.

Robertson, G. P. and P. M. Groffman (2015). Nitrogen Transformations. In E. A. Paul (Ed.), *Soil Microbiology, Ecology, and Biochemistry* (4 ed.)., pp. 341–364. London: Academic Press.

Robertson, G. P. and P. M. Vitousek (2009). Nitrogen in agriculture: Balancing the cost of an essential resource. *Annual Review of Environment and Resources 34*(1), 97–125.

Sandmo, A. (1978). Direct Versus Indirect Pigovian Taxation. *European Economic Review 7*(4), 337–349.

Scott, P. T. (2013). Indirect Estimation of Yield-Price Elasticities. Working Paper.

Segerson, K. (1988). Uncertainty and Incentives for Nonpoint Pollution Control. *Journal of Environmental Economics and Management 15*(1), 87–98.

Shortle, J. S. and R. D. Horan (2001). The Economics of Nonpoint Pollution Control. *Journal of Economic Surveys 15*(3), 255–289.

Sperow, M., M. Eve, and K. Paustian (2003). Potential Soil C Sequestration on US Agricultural Soils. *Climatic Change 57*(3), 319–339.

Stevens, B. K. (1988). Fiscal Implications of Effluent Charges and Input Taxes. *Journal of Environmental Economics and Management 15*(3), 285–296.

Sutton, M. A., O. Oenema, J. W. Erisman, A. Leip, H. van Grinsven, and W. Winiwarter (2011). Too Much of a Good Thing. *Nature 472*(7342), 159–161.

UNEP (2013). Drawing Down N2O To Protect Climate and the Ozone Layer. A UNEP synthesis report, United Nations Environment Programme (UNEP), Nairobi, Kenya.

US EPA (2014). Inventory of US Greenhouse Gas Emissions and Sinks: 1990S2012.

World Bank (2015). World Development Indicators. `http://data.worldbank.org/data-catalog/world-development-indicators` (accessed March 14, 2015).

Xepapadeas, A. (2011). The Economics of Non-Point-Source Pollution. *Annual Review of Resource Economics 3*(1), 355–373.

Yacobucci, B. D., J. L. Ramseur, and L. Parker (2009). Climate Change: Comparison of the Cap-and-Trade Provisions in HR 2454 and S. 1733. Technical Report R40896, Congressional Research Service, Washington, DC.

Table 1: Baseline Input-Output Flows for Production and Consumption (billion $)

A. US

	Endow, Supply	HAY	SB	ETOH	MEAT	F	C	CF	U
L	12,944.7		9.29	5.96	83.6	214.26	9,307.25		3,250
Corn	63.98			16.12	29.43	6.91			
W. Wheat	9.11					4.46			
Sorghum	2.95				1.37				
Cotton	4.99						1.25		
Grass Hay	6.08	6.08							
Alfalfa	7.94	7.94							
Soybean	32.9		19.74						
O	1.66						1.66		
HAY					14.02				
SB					18.87	4.35			
ETOH							22.09		
MEAT					51.75	147.3			
F						88.5		377.29	
C								9,372.71	
CF									9,750

B. ROW

	Endow, Supply	AG, ROW	AG, US	AG	F	C	U	Imports
L	28,992.6	912.6			1,031.13	27,048.87		
A	643.5	257.4					386.1	
Corn			11.52					11.52
W. Wheat			4.65					4.65
Sorghum			1.58					1.58
Cotton			3.74					3.74
Soybean			13.16					13.16
SB			5.81					5.81
AG, ROW				1,170				
AG, US				40.46				
AG					1,210.46			
F							2,241.58	
C							27,008.42	-40.46

Notes: In the US, the value of labor used for agriculture is $74.33 billion. Profit from agriculture, which enters the consumer's income, is $55.3 billion.

Table 2: Marginal Primary Costs

	tE	tN	tN_i	$tN + tA_k$	$tN_i + tA_k$	$tN + tA_{ik}$	$tN_i + tA_{ik}$
2.5% Reduction							
\$/tCO_2e	60.78	84.69	66.20	82.10	64.41	81.27	64.10
ratio to t_E	1.00	1.39	1.09	1.35	1.06	1.34	1.05
N Use (kg/ha)	83.11	81.18	82.64	81.44	82.83	81.51	82.85
% N to N_2O−N	1.79	1.83	1.80	1.82	1.79	1.82	1.79
5% Reduction							
\$/tCO_2e	131.28	187.63	145.63	180.09	140.88	178.01	140.10
ratio to t_E	1.00	1.43	1.11	1.37	1.07	1.36	1.07
N Use (kg/ha)	78.51	74.67	77.50	75.25	77.91	75.39	77.96
% N to N_2O−N	1.85	1.94	1.87	1.93	1.86	1.92	1.86

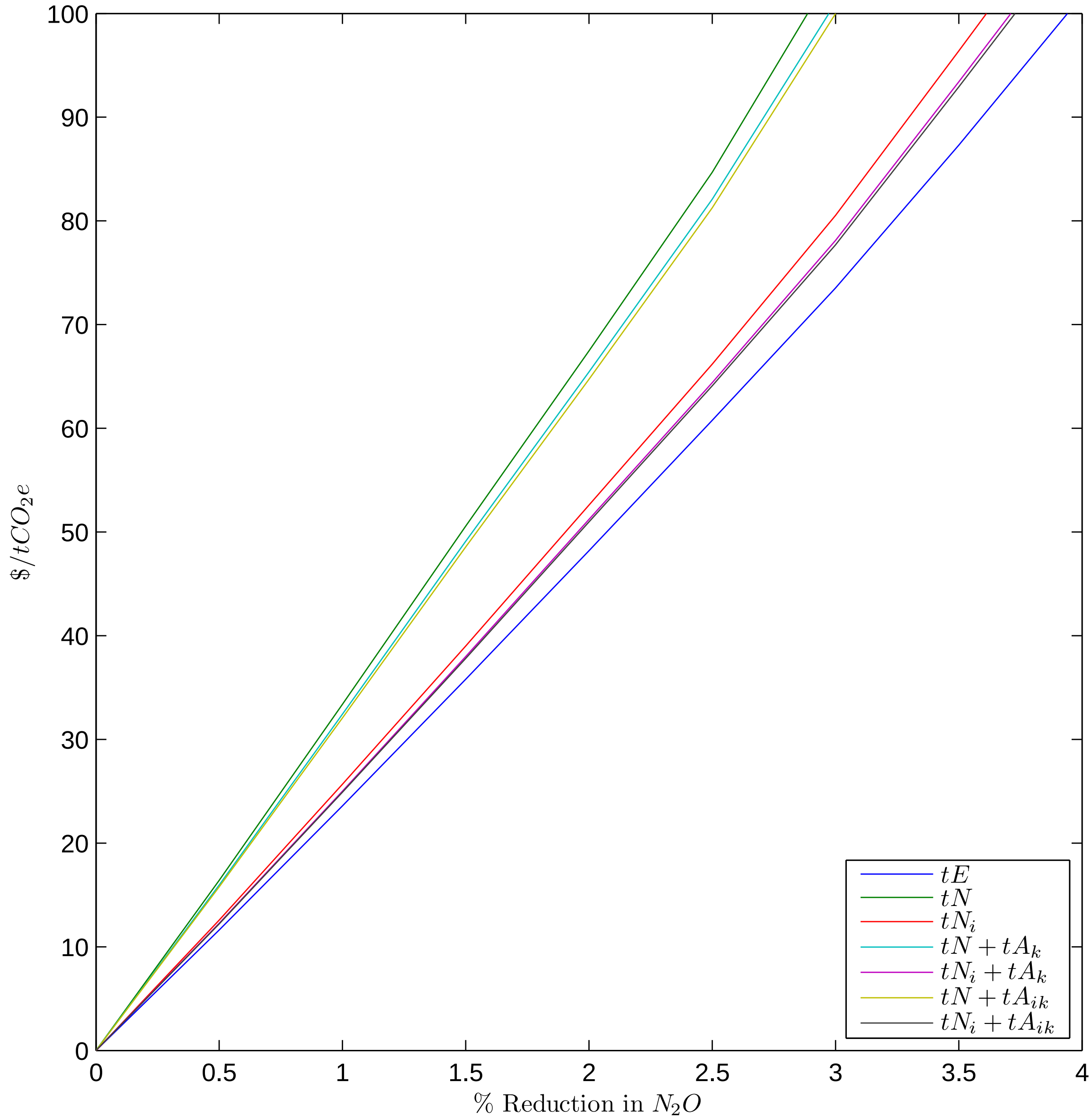
Table 3: Optimal Level of Emission Reductions (%)

Cost of Carbon	tE	tN	tN_i	$tN + tA_k$	$tN_i + tA_k$	$tN + tA_{ik}$	$tN_i + tA_{ik}$
30 \$/tCO_2e	1.27	0.92	1.17	0.94	1.20	0.95	1.21
50 \$/tCO_2e	2.08	1.50	1.92	1.54	1.97	1.56	1.97
90 \$/tCO_2e	3.59	2.61	3.29	2.69	3.38	2.72	3.40

Table 4: Impacts of Alternative Policies

	tE	tN	tN_i	$tN + tA_k$	$tN_i + tA_k$	$tN + tA_{ik}$	$tN_i + tA_{ik}$
2.5% Reduction							
-EV (million $)	55.63	78.13	60.54	75.88	58.97	75.06	58.69
ratio to t_E	1.00	1.40	1.09	1.36	1.06	1.35	1.06
$\Delta\Pi_A$ ($/ha)	-27.95	-3.89	-5.59	-32.01	-28.25	-36.30	-28.75
ratio to t_E	1.00	0.14	0.20	1.15	1.01	1.30	1.03
Δ taxes ($/ha)	43.99	19.70	17.99	52.84	44.99	57.58	45.58
ratio to t_E	1.00	0.45	0.41	1.20	1.02	1.31	1.04
$\Delta\Pi_A + \Delta$taxes ($/ha)	16.04	15.81	12.39	20.83	16.73	21.28	16.83
5% Reduction							
-EV (million $)	232.37	329.74	255.58	318.31	248.03	314.62	246.74
ratio to t_E	1.00	1.42	1.10	1.37	1.07	1.35	1.06
$\Delta\Pi_A$ ($/ha)	-58.47	-6.29	-10.19	-69.06	-59.83	-77.68	-61.03
ratio to t_E	1.00	0.11	0.17	1.18	1.02	1.33	1.04
Δ taxes ($/ha)	92.63	39.93	36.63	113.64	95.70	123.14	97.13
ratio to t_E	1.00	0.43	0.40	1.23	1.03	1.33	1.05
$\Delta\Pi_A + \Delta$taxes ($/ha)	34.16	33.64	26.44	44.58	35.87	45.46	36.09

Figure 1: Marginal Primary Costs



Appendix

A.1 Deriving Analytical Results

A.1.1 First-Best Policies

If fiscal considerations are ignored, the Pigouvian prescription holds in the analytic framework. The social optimum outcome is achieved by setting an emissions tax equal to the marginal damages of emissions.

Suppose the government can implement taxes or subsidies on emissions, t_E, the purchase of n and m, t_N and t_M, and the land allocation, t_k. The first order conditions of the representative consumers problem are:[1]

$$U^k = P_k \quad \forall k \in K \tag{A.1}$$

where U^k is the derivative of the utility function with respect to crop k.

Let y^n_{ijk} and y^m_{ijk} be the derivatives of the yield functions with respect to n and m respectively, and define the superscripted emissions functions in the same manner. Let L^k_{ij} be the derivatives of the land management cost function of parcel ij with respect the land allocated to crop k. Assuming interior solutions for all $\boldsymbol{A}_{ij}$, $\boldsymbol{n}_{ij}$ and $\boldsymbol{m}_{ij}$, the first order conditions for competitive equilibrium are:

$$\begin{aligned}
U^k y^n_{ijk} &= (1+t_N) + t_E e^n_{ijk} \\
U^k y^m_{ijk} &= (1+t_M) + t_E e^m_{ijk} \\
U^k y_{ijk} &= (1+t_N)\, n_{ijk} + (1+t_M)\, m_{ijk} + l_{ijk} + L^k_{ij} + \lambda_{ij} + t_E e_{ijk} + t_k \\
&\qquad \forall i \in I,\ j \in J_i,\ k \in K
\end{aligned} \tag{A.2}$$

and the land constraint for each parcel, where λ_{ij} is the multiplier on the land constraint and derivatives U^k have been substituted in for P_k following equation (A.1).

Social Planner's Problem

Let $\boldsymbol{A}$, $\boldsymbol{n}$ and $\boldsymbol{m}$ be vectors of the land allocations and input use for each crop and parcel. The social planner maximizes utility of the representative consumer by choosing all A_{ijk}, n_{ijk} and m_{ijk} while recognizing that the choices impact emissions:[2]

$$\begin{aligned}
&\max_{\boldsymbol{A},\boldsymbol{n},\boldsymbol{m}} U\left(Y_1, \ldots, Y_K, \bar{L} - M - N - L_A\right) - \phi(E) \\
&\qquad \text{subject to:} \\
&\qquad \sum_k A_{ijk} \leq \bar{A}_{ij} \quad \forall i \in I,\ j \in J_i
\end{aligned} \tag{A.3}$$

where M, N and L_A are the total labor used for crop production defined in Section 3.

[1] The budget constraint is met with equality so $C = \Pi_A + \bar{L} + G - \sum k P_k C_k$, which can be plugged into the utility function.

[2] The land allocation and input rates are the only choice variables because $C_k = Y_k$, Y_k is fully determined by the other variables, and C is the difference in the labor endowment and the total labor inputs to crop production.

The first order conditions of the social planner's problem are:

$$\begin{aligned}
U^k y^n_{ijk} &= 1 + \phi' e^n_{ijk} \\
U^k y^m_{ijk} &= 1 + \phi' e^m_{ijk} \\
U^k y_{ijk} &= n_{ijk} + m_{ijk} + l_{ijk} + L^k_{ij} + \lambda^{SPP}_{ij} + \phi' e_{ijk} \\
&\forall i \in I,\ j \in J_i,\ k \in K
\end{aligned} \tag{A.4}$$

along with the land constraint for each parcel. λ^{SPP}_{ij} are the multipliers on the land constraints.

A emissions tax set equal to the marginal damages of a unit of pollution establishes socially optimal outcomes; if $t_E = \phi'$ and all other taxes are zero then (A.2) match (A.4).

The emissions tax is optimal because it taxes, or subsidizes, all inputs and the land allocated to crop production at the marginal contribution to emissions. Provided these taxes and subsidies can be mimicked, the first-best can be achieved with other policies even if emissions are unobservable.

A.1.2 Derivations of Marginal Welfare Formulas

The indirect utility function, excluding disutility from emissions, is:

$$V\left(P_1 \dots P_K, \Pi_A, G\right) = \max_{C_1,\dots,C_k,C} u(C_1,\dots,C_k,C) + \lambda_I \left[G + \Pi_A + \bar{L} - \sum_k P_k C_k - C\right] \tag{A.5}$$

and from the envelope theorem:

$$\frac{\partial V}{\partial P_k} = -\lambda_I C_k \qquad \frac{\partial V}{\partial \Pi_A} = \frac{\partial V}{\partial G} = \lambda_I. \tag{A.6}$$

Totally differentiating V with respect to a generic policy Ω yields:[3]

$$\begin{aligned}
\frac{dV}{d\Omega} &= \sum_k \frac{\partial V}{\partial P_k}\frac{dP_k}{d\Omega} + \frac{\partial V}{\partial \Pi_A}\frac{d\Pi_A}{d\Omega} + \frac{\partial V}{\partial G}\frac{dG}{d\Omega} \\
&= -\lambda_I \sum_k C_k \frac{dP_k}{d\Omega} + \lambda_I \left(\frac{d\Pi_A}{d\Omega} + \frac{dG}{d\Omega}\right) \\
-\frac{1}{\lambda_I}\frac{dV}{d\Omega} &= \sum_k C_k \frac{dP_k}{d\Omega} - \frac{d\Pi_A}{d\Omega} - \frac{dG}{d\Omega}
\end{aligned} \tag{A.7}$$

where the second line substitutes in the values from equation (A.6).

Likewise, the indirect profit function is:

$$\Pi_A\left(P_1 \dots P_K, \Omega\right) = \sum_{ij}\left(\max_{\boldsymbol{A}_{ij},\boldsymbol{n}_{ij},\boldsymbol{m}_{ij}} \sum_k \pi_{ijk} A_{ijk} - L_{ij} + \lambda_{ij}\left[\bar{A}_{ij} - \sum_k A_{ijk}\right]\right) \tag{A.8}$$

and

$$\frac{\partial \Pi_A}{\partial \Omega} = \sum_{ijk} A_{ijk}\frac{\partial \pi_{ijk}}{\partial \Omega} \qquad \frac{\partial \Pi_A}{\partial P_k} = \sum_{ij} A_{ijk} y_{ijk} = Y_k. \tag{A.9}$$

[3]The policy is assumed to only indirectly impact the consumer through prices, but directly impacts landowners.

The total derivative of profit with respect to the policy is therefore:

$$\frac{d\Pi_A}{d\Omega} = \sum_k \frac{\partial \Pi_A}{\partial P_k}\frac{dP_k}{d\Omega} + \frac{\partial \Pi_A}{\partial \Omega} = \sum_k Y_k \frac{dP_k}{d\Omega} + \sum_{ijk} A_{ijk}\frac{\partial \pi_{ijk}}{\partial \Omega}. \tag{A.10}$$

Recognizing that $Y_k = C_k$ in equilibrium, and plugging equation (A.10) into equation (A.7) yields:

$$-\frac{1}{\lambda_I}\frac{dV}{d\Omega} = -\sum_{ijk} A_{ijk}\frac{\partial \pi_{ijk}}{\partial \Omega} - \frac{dG}{d\Omega} \tag{A.11}$$

which can be used construct the marginal impacts of the policy being analyzed.

Emissions Tax For an emissions tax, $\frac{dG}{dt_E} = t_E\frac{dE}{dt_E} + E$ and $\frac{\partial \pi_{ijk}}{\partial t_E} = e_{ijk}$. Plugging these expressions into equation (A.11) provides:

$$-\frac{1}{\lambda_I}\frac{dV}{dt_E} = -t_E\frac{dE}{dt_E}.$$

Equation (8) is obtained by substituting in the total derivative of emissions with respect to the emissions tax:

$$\frac{dE}{dt_E} = \sum_{ijk} e_{ijk}\frac{dA_{ijk}}{dt_E} + \sum_{ijk} A_{ijk}e^n_{ijk}\frac{dn_{ijk}}{dt_E} + \sum_{ijk} A_{ijk}e^m_{ijk}\frac{dm_{ijk}}{dt_E}$$

along with the relationships $t_E = \frac{P_k y^n_{ijk} - 1}{e^n_{ijk}}$ and $t_E = \frac{P_k y^m_{ijk} - 1}{e^m_{ijk}}$, which are the first order conditions for input use.

Uniform Input Tax For a uniform input tax, $\frac{dG}{dt_N} = t_N\frac{dN}{dt_N} + N$ and $\frac{\partial \pi_{ijk}}{\partial t_N} = n_{ijk}$, so (A.11) becomes:

$$-\frac{1}{\lambda_I}\frac{dV}{dt_N} = -t_N\frac{dN}{dt_N}.$$

Equation (9) is obtained by substituting in the total derivative of N with respect to the input tax:

$$\frac{dN}{dt_N} = \sum_{ijk} n_{ijk}\frac{dA_{ijk}}{dt_N} + \sum_{ijk} A_{ijk}\frac{dn_{ijk}}{dt_N} \tag{A.12}$$

and the first-order conditions for input use $t_N = P_k y^n_{ijk} - 1$.

Acreage Tax In this case, $\frac{dG}{dt_h} = t_h\frac{dA_h}{dt_h} + A_h$ where $A_h = \sum_{ij} A_{ijk}$ and $\frac{\partial \pi_{ijk}}{\partial t_h} = 1$ if $k = h$ and is zero otherwise. Finally, the first order conditions for the land allocation provides the expression $t_h = \pi_{ijk} - L^k_{ij} - \lambda_{ij}$.

A.2 Data

A.2.1 Production and Consumption

General Overview

The value of inputs and output for each intermediate sector and each end use, displayed in Table 1 are established using the end-use shares and the share of labor to the total value of production for each good and by setting the value of labor in aggregate consumption to satisfy the representative consumers' budget constraints. The total value of the endowments are then determined based on assumptions regarding the value of the endowments consumed directly by the representative consumer.

The total value of consumption (CF) in US is set to $9.75 trillion, which is total personal consumption expenditures from 2007 (BEA, 2015). End-use shares for crops and intermediate goods are based on NIPA data and the average of 2006 to 2008 PSD data and more detailed USDA data. To simplify the model, end uses that account for only a small fraction of total production or are economically insignificant are ignored. The share of labor inputs to the value of output for processed soybeans, meat and food is based on NIPA data, while the labor share of ethanol production is set to be broadly consistent with values used in the literature (Plevin and Mueller, 2008; Bento et al., 2015). See section below for more details regarding the construction of the baseline shares. Finally, the ratio of the value of leisure to the value of consumption is set based on the chosen compensated and uncompensated labor supply elasticities.

Total value of consumption in the ROW is $29.25 trillion. This value is based on the assumption that the US accounts for 25% of world GDP, which is broadly consistent with data for the years 2000 to 2010 (World Bank, 2015). The ROW agricultural aggregate is constructed under the assumptions that ROW agricultural production makes up 4% of the total value of consumption (World Bank, 2015), and that the factor share of land in agricultural production is 0.22 (ERS, 2014).[4] The total value of agricultural products in ROW is domestic production plus all imports of crops and intermediate agricultural goods. In the ROW, 40% of the land endowment is used for agricultural production. This is based on FAO statistics for the years 2000 to 2010 for the share of land used for agricultural purposes to total land for all countries except the US (FAO, 2015). The share of labor in food production in ROW is assumed to be the same as in the US.

Baseline Shares

This section describes how input and end-use shares for US intermediate production are constructed from the 2007 Bureau of Economic Analysis NIPA Input-Output tables (BEA, 2015), the USDA's Foreign Agricultural Service Production, Supply and Distribution (PSD) data (FAS, 2015) and other USDA sources.[5] These shares are used to construct the baseline production and consumption data presented in Table 1.

Sector Definitions The industry codes used to define processed soybeans, meat and food sectors in the model are: 1) processed soybeans: 31122A - Soybean and other oilseed processing 2) Meat: 1121A0 - Beef cattle ranching and farming, including feedlots and dual-purpose ranching and farming; 112120 - Dairy cattle and milk production; 112A00 - Animal production, except cattle and poultry and eggs; 311119 - Other animal food manufacturing 3) Food: all industries classified as 311 - Food manufacturing or 312 - Beverage and Tobacco Product Manufacturing, excluding for animal food manufacturing, tobacco manufacturing and industries already included as processed soybeans or meat.

End-use Shares Since the model is static, changes in crop stocks are not considered. On average, stock changes are a relatively unimportant portion of US crop supply for corn, sorghum and soybeans, with the change in stocks making up less than 10% of total consumption for at least nine of the ten years from 2003 to 2010. Stock changes can be much more significant for wheat and cotton, but are associated with unexpectedly low or high production levels. The model reflects long-run average yields, so stock changes

[4]These values are broadly consistent for the time period around 2007. However, the share of agricultural production to ROW GDP is falling over time (World Bank, 2015).

[5]The detailed producer price NIPA IO tables after redefinition are used.

become a less critical portion of total US crop supply. Crop imports to the US are also not included. Hay is largely not traded, and the US is a major net importer of each of the remaining crops. Imports make up less than a 1% share of total domestic consumption for corn, soybeans, sorghum and cotton.[6] Wheat imports are more significant, but make up only about 10% of total US consumption in the years 2006-2008, and a smaller percentage in the years immediately preceding and proceeding years.

Corn is used for ethanol, food, feed (used in meat production) and exported. Feed and export shares are from PSD data. Food and ethanol shares are based on PSD data and consumption end-use data in the USDA Economic Research Service (ERS) Feed Grains Yearbook Tables (ERS, 2015a). In the PSD data, 36% of corn is used for food, seed and industrial uses. The Feed Grains Yearbook data shows that roughly 70% of corn used for food, feed or industrial use goes to ethanol for fuel. This is based on the average of 2006 to 2008. The remainder is assumed to be used for food.[7] All ethanol is assumed to be used in the production of the aggregate consumption good.

Wheat is used in food production or exported. The small portion of wheat production that is used as feed is ignored because it accounts for less than 7% of total consumption between 2006 and 2008. All wheat consumption categorized as "Food, seed or industrial uses" in the PSD data is assumed to go to food production because there are no major industrial uses of wheat.[8]

Soybeans are either exported or processed into meal and oil.[9] Soybean meal and oil are then used as food or feed and can be exported.[10] The vast majority, 75%, of cotton is exported. The remainder is used domestically to produce the composite good.

Based on the NIPA data, 74% of meat production is used in food production. The remainder of meat production is own-used. Likewise, 81% of food production is consumed, while the remainder is own-used. To construct these shares, exports (1.6% for meat 5.6% for food) and other end uses (2% for meat and 20% for food) are ignored.

Labor Shares The share of labor in the total value of processed soybeans, meat and food production are 0.32, 0.42 and 0.46 respectively. These shares represent the total value of inputs from sectors in the NIPA data that are not explicitly represented in the model. For the purposes of calculating labor input shares from the NIPA data, industry codes 1111A0-Oilseed farming, 1111B0-Grain farming and 11900-Other crop farming are assumed to represent the value of crops supplied to the intermediate production sectors and 325190-Other basic organic chemical manufacturing represents ethanol production. The share of labor used in ethanol productions is 0.27, which is broadly consistent with cost estimates for the baseline period and values used in the literature (Plevin and Mueller, 2008; Bento et al., 2015).

A.2.2 Agriculture

Crop and County Coverage

The seven crops encompass the majority of US crop production, accounting for roughly 90% of land allocated to field crops, and 87% of the value of crop production in 2002, 2007 and 2012 according to USDA data (NASS,

[6]Imports of processed soybeans (mean and oil) are also very small less than 1% of US consumption.

[7]A larger share of corn for ethanol is used because in more recent years ethanol production becomes more prominent in later years.

[8]See Table 5 of the USDA's Wheat Data (ERS, 2015b).

[9]Unprocessed soybeans used domestically as animal feed are ignored because this end use accounts for less than 4% of total consumption between 2006 and 2008.

[10]Soybean oil used for industrial purposes is not considered because it is less than a 3% of total processed soybean output.

2014). Only the most significant crop variety in terms of land shares and quantities is modeled. Therefore, cotton represents upland cotton and wheat represents winter wheat. Upland cotton has made up more than 97% of total land planted to cotton in each year between 2000 and 2013 (NASS, 2014). Pima cotton made up more than 10% of cotton acres in only New Mexico and California, both of which account for less than 3% of total land allocated to cotton. Winter wheat accounted for more than 69% of total wheat in each year from 2000 to 2014. Over this same time period, durum wheat never accounted for more than 5% of total wheat acres, while spring wheat accounted for approximately 25% of total wheat acres.

Counties must meet two criteria based on the quantity of land allocated to the seven modeled crops to be included in the model. First, only counties located in states that contain more than 0.25% of total land allocated to the modeled crops in both 2007 and 2012 are included. This criteria drops 13 states from the analysis, but only a very small portion, less than 1.5%, of land allocated to the modeled crops.[11] Second, counties must contain more than 10,000 hectares of land allocated to the modeled crops in 2007 or 2012. There are 864 counties within the included states that fail to meet this criteria, but these dropped counties accounted for less than 3% of total land allocated to the modeled crops in the included states.

Irrigated agriculture is modeled in counties if the share of irrigated cropland is at least 5% of total land. Rainfed agriculture is not modeled in counties with more than 90% irrigated cropland. Just under 90% of irrigated cropland in the modeled counties and crops is accounted for with these assumptions.

Yields, Inputs and Costs

County level yields for rainfed and irrigated crop production are from the Census of Agriculture. These county level values, along with county level harvested crop shares are used to calculate state and regional average yields for each crop and irrigation category for the counties included in the model. These aggregate statistics are used along with Daycent output to calibrate the yield functions that enter the economic model.

N fertilizer application rates for rainfed and irrigated corn, soybeans, wheat, cotton and sorghum are calculated from multiple survey years of state level ARMS data. State level application rates are calculated from the ARMS data by multiplying the percent of acres treated with N fertilizer by the units of N applied per unit land. Since the ARMS breaks down farms by irrigation system, application rates for irrigated crop production are a weighted average rates for farms with gravity or pressure irrigation systems. The application rates used in the model are averages across each available survey year between 2002 and 2012.[12] Since grass hay is not covered by ARMS, N application rates by region for grass hay are from the FASOM model data set, which was used to conduct the EPA's Regulatory Impact Assessment of the expanded Renewable Fuel Standard program (Beach et al., 2010). Legume hay is assumed to receive no N fertilizer.

County level data on yields and application rates are required for any county, irrigation category and crop that is included in the model, but for which the N choice is not modeled. If county level data is not available, the first available average data from the state, region, or national level is used.

Productions costs for corn, soybeans, wheat, cotton, and sorghum are based on data from the Commodity Costs and Returns. Total production costs are calculated as the sum of all items designated operating costs plus the costs from hired labor, capital recovery on machinery, taxes and insurance and general farm

[11] The states dropped are Arizona, Connecticut, Delaware, Florida, Maine, Massachusetts, Nevada, New Hampshire, New Jersey, New Mexico, Rhode Island, Vermont and West Virginia. The model focuses on the continental US, so Alaska and Hawaii are not included.

[12] The 2002 survey year is included so that at least two survey years will be used to construct the average application rates. The two most recent available soybean survey years are 2002 and 2006.

overhead.[13] The cost of purchased irrigation water is included only for irrigated crops. The Commodity Costs and Returns data is available for nine Farm Resource Regions and at the national level. Cost data is assigned to counties based on Farm Resource Region designation. If no cost data is available at the Farm Resource Region for a particular county and crop, then the national average values are used.

Labor inputs to agriculture, l_{ijk}, are total costs less the costs of N fertilizer, which are calculated using the Daycent yield functions and baseline prices for crops and N.

A.2.3 Prices

Baseline prices are reported in Table A.2. Crop prices are calculated from the national prices reported in the NASS annual surveys. The price of N is calculated from the national price of anhydrous ammonia. In the model, N represents nutrient N as opposed to N fertilizer material. The price of nutrient N is calculated as the price of anhydrous ammonia divided by the nutrient N content of anhydrous ammonia, 0.8. All other prices are normalized to one in the baseline.

A.3 Biophysical Model

To generate a data set from which the yield and emissions functions can be estimated, Daycent simulations were conducted for a large sample of agricultural sites across the US. Sites are selected from points in the Natural Resource Inventory (NRI), a rotating panel sample of all non-federal land (USDA-NRCS, 2009). Site specific data on historic land use, cropping patterns and management practices from the NRI, soil attributes from the Soil Survey Geographic Database (SSURGO) and gridded daily weather from the North America Regional Reanalysis (NARR) products are inputs to the Daycent simulations. Yields and emissions are simulated for a 30 year period following changes in crop or management practice.

Linear mixed effects models were used to estimate the relationships between Daycent model outputs, yields and emissions, and crop and management choices and site characteristics. Separate models were estimated for broad regions defined in Table A.1. The dependent variables in these regression models are the carbon content of grain and straw yields, the flux of N_2O, N volatilized as NO_x and NH_3, and N leached as NO_3.[14] The explanatory variables in the regression models include N applied and N applied squared, organic amendments and organic amendments squared, the crop residue removal rate, dummy variables for crop, tillage, irrigation status and fertilizer timing and site specific average temperature, a soil moisture index and soil sand fraction and first order interactions between all variables.[15]

An adjusted set of yield functions for use in the economic model are derived from the estimated yield functions, which are of the form $y = \beta^0 + \beta^1 n + \beta^2 n^2$. The yield functions that enter the economic model are calibrated so that, given baseline prices, the yield and N input rate predictions of the economic model match baseline economic data at the regional level, while the Daycent yield functions drive the heterogeneity in yields and optimal N application rates at the parcel level. For each region, crop and irrigation status the distribution of β^2s is shifted so that average N application rates predicted by the economic model match observed average N application rates. Given the shifted β^2s, the distribution of β^0s is shifted so that yields at the optimal N application rates match observed yields by region, crop and irrigation status.

[13] Operating cost categories include: seed, fertilizer, soil conditioners, manure, chemicals, custom operations, fuel, lube and electricity, repairs, purchased irrigation water, commercial drying, ginning, straw baling and interest on operating capital.

[14] Although Daycent tracks daily emissions values, annual totals are used for this analysis.

[15] Explanatory variables are dropped from the models if the coefficients are not significant and the variable does not greatly improve overall model fit.

N application rate decisions are not modeled in the county-crop combinations for which yields are unresponsive to N. Therefore, the N application rate decisions are not modeled for the legume crops: soybeans and legume hay. N application rate decisions are also not modeled for a parcel-crop combination ijk if β^2_{ijk} falls in the lowest 1% of all β^2s. For any ijk where the N application decision is not modeled N application rates are fixed at observed baseline levels. The crop choice decisions is still modeled in these counties. In total, 10,444 crop/counties combinations are included in the model, with the N application rate decision modeled in 6,748 crop/counties.

References

BEA (2015). US Department of Commerce, Bureau of Economic Analysis, Industry Data, Input-Output. http://www.bea.gov/iTable/index_industry_io.cfm (accessed March 14, 2015).

Beach, R. H., D. Adams, R. Alig, J. Baker, G. S. Latta, B. A. McCarl, B. C. Murray, S. K. Rose, and E. White (2010). Model Documentation for the Forest and Agricultural Sector Optimization Model with Greenhouse Gases (FASOMGHG), Draft Report.

Bento, A. M., R. Klotz, and J. R. Landry (2015). Are there Carbon Savings from US Biofuel Policies? The Critical Importance of Accounting for Leakage in Land and Fuel Markets. *The Energy Journal 36*(3).

ERS (2014). International Agricultural Productivity. http://www.ers.usda.gov/data-products/international-agricultural-productivity.aspx (accessed March 19, 2015).

ERS (2015a). US Department of Agriculture, Economic Research Service, Feed grains: Yearbook Tables. http://www.ers.usda.gov/data-products/feed-grains-database/feed-grains-yearbook-tables.aspx (accessed March 14, 2015).

ERS (2015b). US Department of Agriculture, Economic Research Service, Wheat Data. http://www.ers.usda.gov/data-products/wheat-data.aspx (accessed March 14, 2015).

FAO (2015). FAOSTAT. http://faostat3.fao.org/home/E (accessed May 8, 2015).

FAS (2015). US Department of Agriculture, Foreign Agricultural Service, Production, Supply and Distribution Online. http://apps.fas.usda.gov/psdonline/psdHome.aspx (accessed March 14, 2015).

NASS (2014). US Department of Agriculture, National Agricultural Statistics Service, Quick Stats. http://quickstats.nass.usda.gov/ (accessed September 8, 2014).

Plevin, R. J. and S. Mueller (2008). The Effect of CO_2 Regulations on the Cost of Corn Ethanol Production. *Environmental Research Letters 3*(2), 024003.

USDA-NRCS (2009). Summary Report: 2007 National Resources Inventory. Technical report, Natural Resources Conservation Service, Washington, DC.

World Bank (2015). World Development Indicators. http://data.worldbank.org/data-catalog/world-development-indicators (accessed March 14, 2015).

Table A.1: Region Designations

Corn Belt
460 total counties, 460 with rainfed land and 42 with irrigated land
States: Illinois, Indiana, Iowa, Missouri, Ohio
Crops: Corn, W. Wheat, Cotton, Grass Hay, Alfalfa, Soybean

Plains
311 total counties, 309 with rainfed land and 150 with irrigated land
States: Kansas, Nebraska, North Dakota, South Dakota
Crops: Corn, W. Wheat, Sorghum, Grass Hay, Alfalfa, Soybean

Lake States
194 total counties, 194 with rainfed land and 34 with irrigated land
States: Michigan, Minnesota, Wisconsin
Crops: Corn, W. Wheat, Grass Hay, Alfalfa, Soybean

Northeast
103 total counties, 103 with rainfed land and 5 with irrigated land
States: Maryland, New York, Pennsylvania
Crops: Corn, W. Wheat, Grass Hay, Alfalfa, Soybean

Pacific Northwest
40 total counties, 37 with rainfed land and 32 with irrigated land
States: Oregon, Washington
Crops: Corn, W. Wheat, Grass Hay, Alfalfa

California
20 total counties, 16 with rainfed land and 20 with irrigated land
States: California
Crops: Corn, W. Wheat, Cotton, Grass Hay, Alfalfa

Mountains
150 total counties, 124 with rainfed land and 130 with irrigated land
States: Colorado, Idaho, Montana, Utah, Wyoming
Crops: Corn, W. Wheat, Sorghum, Grass Hay, Alfalfa, Soybean

South Central
291 total counties, 291 with rainfed land and 80 with irrigated land
States: Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Tennessee, Texas
Crops: Corn, W. Wheat, Sorghum, Cotton, Grass Hay, Alfalfa, Soybean

Southeast
177 total counties, 177 with rainfed land and 60 with irrigated land
States: Georgia, North Carolina, South Carolina, Virginia
Crops: Corn, W. Wheat, Cotton, Grass Hay, Alfalfa, Soybean

Southwest
222 total counties, 222 with rainfed land and 86 with irrigated land
States: Oklahoma, Texas
Crops: Corn, W. Wheat, Sorghum, Cotton, Grass Hay, Alfalfa, Soybean

Texas is listed under both South Central and Southwest because a portion of eastern Texas is designated as South Central.

Figure A.1: Included Counties by Region

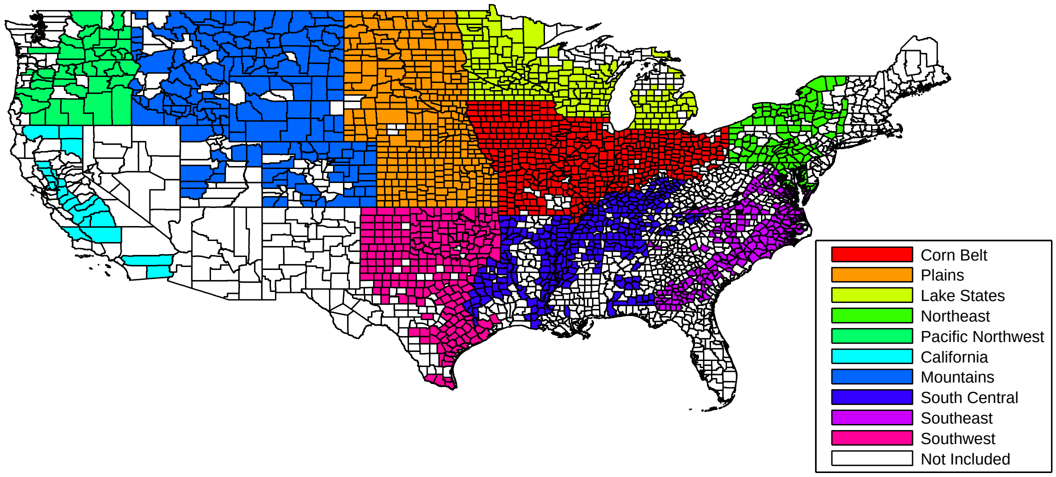


Figure A.2: Included Counties by Irrigation Category

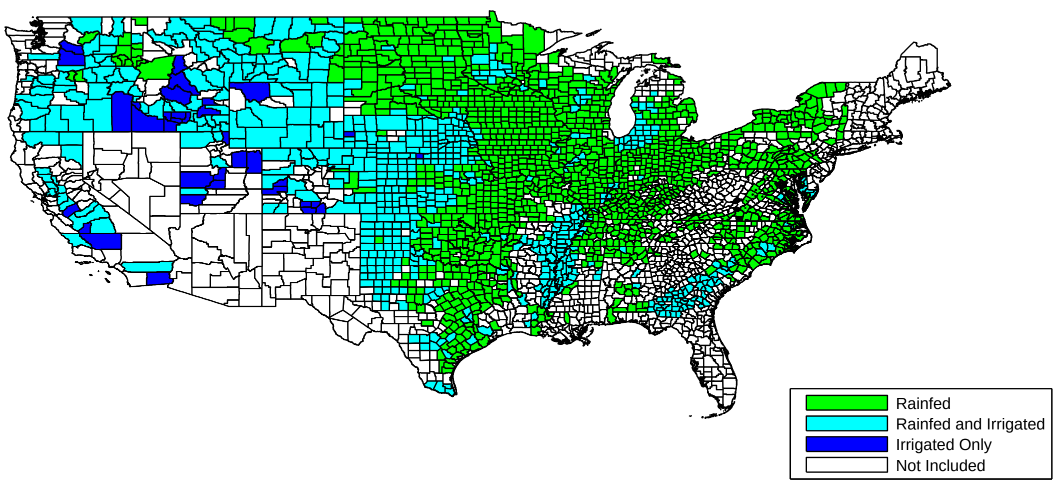


Table A.2: Baseline Prices

Product	Value	Unit
Corn	197.50	\$/t
W. Wheat	227.44	\$/t
Sorghum	182.65	\$/t
Cotton	1576.30	\$/t
Grass Hay	127.92	\$/t
Alfalfa	173.43	\$/t
Soybean	415.57	\$/t
N	0.92	\$/kg N

Table A.3: Baseline Crop Production by Region (Million Hectares)

Region	Corn	W. Wheat	Sorghum	Cotton	Grass Hay	Alfalfa	Soybean
Corn Belt	16.05	0.96		0.15	1.70	0.69	12.99
Plains	8.37	4.91	1.06		2.23	1.90	6.29
Lake States	5.53	0.26			0.43	1.08	4.07
Northeast	0.79	0.15			0.73	0.32	0.46
Pacific Northwest	0.06	0.97			0.29	0.31	
California	0.07	0.10		0.07	0.18	0.36	
Mountains	0.51	2.03	0.06		0.92	1.70	0.00
South Central	1.83	0.76	0.18	0.92	2.41	0.09	3.22
Southeast	0.72	0.43		0.76	0.63	0.02	0.99
Southwest	0.81	2.63	0.94	1.65	2.42	0.13	0.11
Total	34.73	13.21	2.24	3.55	11.93	6.60	28.13

Table A.4: Baseline N_2O Emission Rates ($MgCO_2e/ha$)

Region	Corn	W. Wheat	Sorghum	Cotton	Grass Hay	Alfalfa	Soybean
Corn Belt	1.28	0.54		0.83	1.15	0.52	0.75
	(0.95, 1.47)	(0.50, 1.05)		(0.82, 0.84)	(1.10, 1.28)	(0.49, 0.54)	(0.68, 0.85)
Plains	0.62	0.26	0.33		0.71	0.50	0.44
	(0.47, 1.19)	(0.25, 0.55)	(0.29, 0.44)		(0.51, 1.08)	(0.38, 0.85)	(0.30, 0.80)
Lake States	0.99	0.50			1.07	0.48	0.73
	(0.83, 1.10)	(0.49, 0.95)			(0.90, 1.16)	(0.38, 0.53)	(0.62, 0.86)
Northeast	0.76	0.48			0.85	0.56	0.69
	(0.58, 0.90)	(0.44, 0.64)			(0.61, 0.92)	(0.42, 0.66)	(0.55, 0.84)
Pacific Northwest	0.79	0.20			0.68	0.60	
	(0.55, 0.80)	(0.17, 0.52)			(0.48, 0.82)	(0.38, 0.66)	
California	0.85	0.58		0.81	0.81	0.62	
	(0.38, 0.88)	(0.35, 0.70)		(0.75, 0.86)	(0.44, 1.02)	(0.38, 0.67)	
Mountains	0.66	0.35	0.29		0.84	0.45	0.51
	(0.24, 0.94)	(0.27, 1.05)	(0.25, 0.63)		(0.47, 1.46)	(0.25, 0.71)	(0.41, 0.85)
South Central	0.99	0.44	0.49	0.70	0.97	0.39	0.50
	(0.83, 1.42)	(0.37, 0.70)	(0.36, 0.71)	(0.48, 1.21)	(0.44, 1.36)	(0.30, 0.68)	(0.33, 0.76)
Southeast	0.74	0.41		0.58	0.79	0.45	0.50
	(0.64, 0.94)	(0.36, 0.67)		(0.50, 0.69)	(0.70, 0.82)	(0.39, 0.51)	(0.36, 0.55)
Southwest	0.77	0.36	0.36	0.48	0.87	0.98	0.63
	(0.62, 0.95)	(0.33, 0.85)	(0.32, 0.54)	(0.40, 0.65)	(0.80, 1.14)	(0.88, 1.52)	(0.58, 1.11)
National	1.01	0.34	0.36	0.58	0.89	0.51	0.64

Notes: Average emissions rates calculated using predicted N application rate at baseline prices. Values in parenthesis are lowest and highest county emissions rates within a region.