Regulating Greenhouse Gas Emissions in Sectors Exempt from Climate Policy*

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Abstract

This paper compares the performance of policy instruments for reducing greenhouse gas emissions (GHG) in sectors that are exempt from climate change regulation. I focus on two constraints that can justify exemption: unobservable emissions and/or distributional concerns regarding impacts on firms' profit. My analysis is conducted in the context of nitrous oxide (N_2O) emissions from US agriculture, a substantial source of GHGs that has never been regulated, using an integrated general equilibrium and biophysical framework. Leveraging the biophysical model allows the framework to represent key drivers of policy costs, heterogeneity in productivity and emissions rates, at a fine spatial resolution. I uncover a tension in the policy instrument choice problem; policy options recommended for reducing the costs of addressing an unobservable source of emissions can have more prominent impacts on profit. In fact, if the agricultural sector is compensated for changes in profit using a costly lump sum transfer, input-based policies can be the least cost policy options even if an emissions tax is available. Results also inform the debate regarding agriculture's role in climate policy. Input-based policies can reduce N_2O with primary costs approaching a first-best policy. For a 5% reduction in N_2O, the primary costs of uniform and non-uniform input taxes range from 11% to 56% more expensive than an emissions tax. However, the relative inefficiency of the input taxes can be much larger, as much as 140% more costly than the emissions tax, if gross costs are considered.

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1 Introduction

The marginal costs of abatement of all emitting sources must be equalized in order to efficiently regulate a global pollutant. Yet, proposed and enacted climate change legislation, such as carbon tax or cap and trade programs, violates this principle by leaving sectors that are significant sources of greenhouse gas (GHG) emissions unregulated.[1] Provided the broader climate program can be adjusted, reducing emissions in an exempt sector is a potential approach to lowering the overall costs of climate action. The policy instrument choice problem in this context is inherently second best (Lipsey and Lancaster, 1956) because it faces the same constraints that justified the sector being exempt from climate regulation in the first place.

Unobservable emissions and distributional concerns are two prominent constraints that may preclude a sector from being covered by climate change legislation.[2] If a sector's emissions are unobservable, or prohibitively costly to monitor, then direct emission regulations, such as a carbon tax or quota, are not feasible. Policymakers must instead choose from alternative, and likely inefficient, instruments that regulate observable quantities.[3] If a sector's stakeholders wield substantial political influence, regulators may be hesitant to enact a policy that is perceived to harm the sector (e.g. reduce profit). Distributional concerns can motivate the choice of a policy that may not be supported on efficiency grounds (Buchanan and Tullock, 1975).

The primary goal of this paper is to explore the performance of policy instruments for reducing emissions in sectors exempt from climate change regulation due to unobservable emissions and distributional concerns. I analyze the costs of policy options for reducing emissions from an unobservable source when, due to distributional concerns, the regulator seeks to limit adverse impacts to the regulated sector. To formalize the regulator's distributional concerns, I impose the requirement that the regulated sector is compensated for any change in profit caused by the environmental policy, which will affect gross costs by inducing changes to the distortionary tax system.[4] This allows the estimates of gross costs to capture the distributional concern and for instruments to be directly compared.

In this setting, it is unclear which policy instrument will achieve emissions reductions at least cost. The

[1]For example, the GHG cap and trade program proposed in the American Clean Energy and Security Act of 2009, the "Waxman-Markey" climate bill, covered primarily large stationary source that could be attributed 25,000 tCO_2e per year. Between 2012 and 2015, covered entities would have accounted for only 72-78% of US emissions (CBO, 2009).

[2]Pooley (2010, pp. 390-394) emphasizes the political influence of agriculture stakeholders in the debates surrounding Waxman-Markey. See Bohringer and Rutherford (1997) for a discussion of carbon tax exemptions for energy-intensive or export-based sectors. They find that exempting sectors responsible for only 12% of baseline emissions raises the costs of achieving a 30% cut in emissions by around 20%.

[3]Although it is theoretically possible to achieve socially optimal outcomes without observing emissions, implementation is unlikely to be practically feasible (see (Griffin and Bromley, 1982; Fullerton and West, 2002)). One takeaway of these papers is that unless policies can be differentiated across polluting sources, the socially optimal outcome can only be achieved under very restrictive assumptions regarding regulated entities' technology, behavior and emissions schedule.

[4]The compensation requirement is similar in nature and implementation to the "equity value neutrality" constraint studied by Bovenberg et al. (2005) and Bovenberg et al. (2008).

performance of policy instruments suitable for addressing an unobservable source of emissions, such as input taxes or restrictions, is theoretically ambiguous and depends heavily on the characteristics of the regulated firms (Helfand and House, 1995; Fullerton and Gan, 2005). Likewise, policies induce differential impacts on regulated firms' profit based on abatement actions undertaken, the revenue collected by the policy, and any output price response (Stevens, 1988; Buchanan and Tullock, 1975). Considering unobservable emissions and profit impacts jointly implies a tension between efficiency and distributional concerns through at least two channels. First, policies that induce larger than optimal increases in output prices will lead to relatively high efficiency costs and profit. Second, policies that raise revenue, such as an input tax, will likely have lower costs than an equivalent quantity policy, such an input rate restriction, if the revenues can be used to alleviate distortions elsewhere in the economy (Goulder, 1995). However, the input tax will result in a larger reduction in firms' profit because it raises the costs of all units of the input, whereas the input rate restriction only affects profits through the change in input use (Buchanan and Tullock, 1975). I explore the tradeoffs between alternative policies by calculating the costs of emissions reductions for a variety of instruments, with and without the compensation requirement in place. Through this analysis, I am also able to evaluate if either constraint, unobservable emissions or distributional concerns, warrant leaving a sector unregulated for climate purposes.

My analysis focuses on policies to reduce GHG emissions from the agricultural sector. Indeed, a secondary goal of this paper is to provide national-scale cost estimates for policies to reduce agricultural emissions. The motivation for focusing on the agricultural sector is straightforward. The sector contributes 12% of annual global emissions (IPCC, 2014) and is often a predominant share of emissions exempt from climate regulations.[5] Designing policies to reduce agricultural emissions is complicated by unobservable emissions and distributional concerns. GHG emissions from agriculture depend on the production decisions of many farmers who face heterogeneous weather and soil characteristics. Absent continuous field-level monitoring, which is prohibitively costly (Hensen et al., 2013), agricultural emissions are unobservable. Agricultural stakeholders wield a unique political influence and policymakers continue to protect the sector (Bellemare and Carnes, 2015). In spite of these complications, there have been prominent calls for reducing emissions from agriculture (IPCC, 2014; UNEP, 2013). However, national-scale estimates of the costs of agricultural mitigation policies are sparse, calculate only primary costs and focus on unfeasible emissions-based policies (McCarl and Schneider, 2001; De Cara et al., 2005).

To this end, I use analytical and numerical general equilibrium models to evaluate the costs of reductions in the primary source of GHGs from US agriculture, nitrous oxide (N_2O) emissions from cropland

[5] Under Waxman-Markey, agriculture would have made up around 30% of excluded emissions, based on the 72% of US emissions covered by the program (CBO, 2009) and 8% of total US emissions attributable to agriculture (EPA, 2014).

agriculture (EPA, 2014), with and without the requirement that the agricultural sector is compensated for changes in profit.[6] The models capture the primary channels through which farmer decisions affect N_2O emissions, crop choice and mineral nitrogen (N) application rates (Millar et al., 2010; Ribaudo et al., 2011), and account for the heterogeneity in yields and emissions rates that is a key determinant of the performance of alternative policies. Farmers managing fixed parcels of land with heterogeneous quality (capturing both soil and climate characteristics) choose N application rates and the share of land to allocate to a set of crops to maximize profit. Yield and emissions for each crop are functions of N rates and depend on a parcel's land quality. A representative consumer demands crops and a composite good, and supplies labor based on the real wage. The government sets environmental policies and compensation levels, which are implemented as lump sum transfers to the agricultural sector, and maintains a balanced budget by adjusting a preexisting tax on labor.

With the analytical model, I assess the gross costs associated with a marginal change in three simple mitigation policy instruments, an emissions tax, an input tax and an input rate restriction. I decompose the change in gross costs into primary costs, which reflect input and land allocation effects, the standard tax interaction and revenue recycling effects and a compensation effect. These decompositions provide intuition regarding the margins of adjustments that drive gross costs and how heterogeneity in production characteristics affects the performance of the alternative instruments.

The numerical model is a national-scale integrated biophysical and general equilibrium framework that accounts for agricultural production decisions at the county level and prices and consumer decisions at the national level. To date, it is the most comprehensive framework for estimating the costs of N_2O mitigation policies and, to my knowledge, the first attempt to integrate a detailed agricultural sector into a general equilibrium framework similar to those used to analyze environmental policy choice (e.g. Goulder et al. (1999)), which endogenize labor supply and the public sector. The model represents the production of seven crops in nearly 2,000 counties across 35 states, covering 90% of US cropland allocated to field crops. To accurately represent the heterogeneity in yield and emission functions at the county scale, I rely on a unique dataset of biophysical model output that provides information on marginal yields, emissions rates and marginal emissions rates, none of which could be recovered from observational data for the required spatial coverage.

Using the numerical model I compute national-scale estimates for the costs of mitigation policies that account for the significant heterogeneity in yields and emissions functions across crops and space, and

[6] Agricultural N_2O emissions make up more than half of total agricultural greenhouse gas emissions in the US and are of the same, or larger, magnitude as emissions from oil combustion by industrial sources, natural gas use by residential sources, CO_2 from aviation and methane from livestock operations (EPA, 2014). Due to the magnitude of these emissions, there is substantial interest in policy options to reduce agricultural N_2O (Reay et al., 2012; UNEP, 2013). Yet, to date, comprehensive estimates of the costs of reducing N_2O are limited.

both detailed farm-scale adjustments and equilibrium changes in the prices of crops and food. Relative to the analytical model, it also allows me to consider more complicated policy configurations and non-marginal reductions in N_2O. I calculate the costs of achieving targeted levels of emissions reductions using an emissions tax, and a range of policies suggested for addressing unobservable sources of emissions: uniform and non-uniform taxes on N fertilizer, high and low cost restrictions on N application rates, and a combination of non-uniform N and crop acreage taxes.

I draw four main takeaways from my analysis. First, policies that regulate easily observable quantities can reduce agricultural N_2O at costs approaching those of a first-best policy. Consistent with earlier work (McCarl and Schneider, 2001), I find that the economic potential for reducing agricultural N_2O is modest. A 5% reduction in N_2O, roughly 8 $TgCO_2e$, can be achieved with marginal primary cost of approximately 30 $\$/tCO_2e$ using an emissions tax. Unlike previous work, I provide national-scale primary cost estimates for implementable alternative policies that do not require emissions to be monitored. Although a uniform tax on N and input rate restrictions are prohibitively costly, around 50% higher marginal primary costs than the emissions tax for a 5% reduction in N_2O, the non-uniform N tax and the combination of the non-uniform N tax and a crop acreage tax are only 15% and 11% more expensive than the emissions tax. Based on primary costs, non-uniform and combinations of input taxes appear to be reasonable replacements for an emissions tax. Cost estimates of this nature would be difficult to obtain from more aggregate frameworks or reduced form methods, since the within-region variability in yields and emissions rates obtained from the biophysical model drives the cost differences between the emissions tax and the non-uniform input taxes.

Second, primary cost estimates, generally used to evaluate agri-environmental policies, can provide misleading estimates of the social cost of alternative mitigation policies. Gross costs can fall above or below primary costs, and may even be negative (signifying an increase in welfare). For the emissions tax, primary costs for a 5% reduction in emissions are \$111 million while gross costs are -\$461 million. The reason for negative gross cost is the presence of land as a fixed factor of production. Since land generates profits that are not fully taxed, the environmental taxes serve as surrogate profit taxes that shift the burden of taxation away from labor to land (Bento and Jacobsen, 2007). Although the ordering of policies based on gross costs are nearly unchanged from those based on primary costs, the differences in gross costs relative to the emissions tax tend to be much larger. For a 5% reduction in N_2O, the gross costs of the uniform and non-uniform N taxes are at least twice as large, and the input rates restrictions approaching three times as large, as the emissions tax. These large differences occur because the alternative policies generate less revenue than the emissions tax or no revenue at all. In contrast, the combination of non-uniform N and acreage taxes is relatively more cost effective because the acreage taxes are a close replacement for a profit tax.

Third, the compensation requirement dramatically changes the ranking of policy instruments based on gross costs. Strikingly, the emissions tax is no longer always the least cost policy. In fact, at a 5% reduction, all policies except the high cost input restriction and non-uniform N tax outperform the emissions tax. This result mirrors Bovenberg et al. (2008) who show that with compensation constraints in place a technology mandate and performance standard can outperform an emissions tax. I show that different configurations of input taxes can also dominate an emissions tax. The gross cost with compensation results illustrate how profit concerns complicate general advice regarding policy instrument choice in the presence of unobservable emissions. Strategies suggested for reducing the primary costs of regulating unobservable emissions may increase or decrease gross costs when the compensation requirement is imposed.

Finally, in the context of agricultural N_2O, neither unobservable emissions nor profit considerations seem to justify leaving the sector unregulated for climate purposes. Observing emissions does not meaningfully lower costs. If profit impacts are not a concern, then taxes on easily observable quantities can match the performance of an emissions tax in terms of primary or gross costs. If profit impacts are a concern, then observing emissions may be unnecessary. For modest cuts in emissions each of the alternative taxes and the low cost restriction dominate the emissions tax if compensation is in place. Concerns over the impacts of climate legislation on the welfare of the agricultural sector may be unfounded. Since agriculture production relies heavily on fixed factors of production and faces inelastic demand for its products, profits stand to increase in response to climate legislation. To the extent that profits to land owners reflect the well-being of the agricultural sector, mitigation policies may actually benefit the sector.

The rest of the paper is organized as follows. In the next Section I discuss the relationship between my work and previous literature on environmental policy choice and agricultural mitigation. In Section 3 I provide background on the biophysical and management drivers of agricultural N_2O. The analytical model and decompositions of primary and gross costs are presented in Section 4. I lay out the numerical model, discuss data and calibration, and present numerical results in Sections 5, 6 and 7 respectively. Section 8 concludes.

2 Relation to Prior Literature

This paper builds on broad sets of literature focused on designing environmental policies in second-best settings and evaluating the costs of reducing GHGs from agriculture.

Policy Choice in Second-best Settings

The three defining characteristics of the policy choice problem addressed in this paper are unobservable emissions, compensation requirements for changes in the regulated firms' profit, and a preexisting distortionary tax system which is adjusted to fund compensation. Streams of literature on environmental policy choice in second-best settings provide guidance regarding the influence of each characteristic on policy choice, but this is the first paper to directly evaluate the costs of environmental regulation in the presence of all three characteristics. By accounting for all three characteristics in a single setting, I am able to provide a rich analysis of the potential costs of mitigation policies, and to explore which characteristic has the largest impact on the costs of emissions reductions.

When emissions are unobservable, the theoretical literature suggests that a range of policies based on observable quantities could be applicable. 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 that lead to emissions can be more cost effective. When there are a large number of heterogeneous pollution sources, non-uniform or multipart instruments are likely to be more efficient than single, uniform regulations of observable factors (Fullerton and West, 2002; Griffin and Bromley, 1982).[7] In fact, first-best outcomes can be achieved with sufficiently differentiated tax rates or complex multipart instruments, but may be impractical due to extreme information requirements or high implementation costs. The inefficiency of alternative policies, relative to an emissions tax, is theoretically ambiguous, and depends on the channels through which a policy induces abatement and the heterogeneity of affected firms' technology and emissions schedules (Helfand and House, 1995; Fullerton and Gan, 2005; Fullerton and West, 2010; Knittel and Sandler, 2013).

A large body of research has emphasized that the gross costs of environmental policies may be drastically affected by preexisting distortionary taxes, such as an income tax (see Goulder (1995) for an introduction and summary). Gross costs consists of primary costs, which is the standard Harberger triangle measuring deadweight loss in the regulated market, and two additional effects. The tax interaction effect captures the efficiency losses that are incurred as the environmental program exacerbates the preexisting distortion, typically through changes in the real wage. The revenue recycling effect accounts for efficiency gains from alleviating the preexisting distortion using revenues from the environmental program. Most studies in this area analyze the case where the tax system is optimal in the baseline and find that preexisting taxes elevate the gross costs of environmental policies because the tax interaction effect dominates the revenue recycling

[7]The inability to observe firms' emissions is a key feature of non-point source pollution from agriculture. There is a long and detailed literature on policy instrument choice in this setting, see Shortle and Horan (2001) or Xepapadeas (2011) for reviews. Non-point source pollution policies must also address the stochastic nature of emissions and marginal damages varying across sources, but may be able to exploit observable ambient pollution levels (Segerson, 1988).

effect. Bento and Jacobsen (2007) show that the presence of a fixed factor of production, such as land, may reverse this result. Profit generated by a fixed factor would be fully taxed in an optimal tax system, but this is unlikely to occur in practice. An environmental policy that serves as a surrogate for the missing profit tax can therefore improve the efficiency of the tax system by shifting the burden of taxation towards the fixed factor.

The distributional impacts of climate policy have also received significant attention, particularly with regards to the regressivity of a carbon tax (Dinan, 2012; Fullerton et al., 2012; Williams et al., 2014).[8] A related set of papers focuses on alleviating the impacts of environmental programs on regulated firms. Bovenberg et al. (2005) and Bovenberg et al. (2008) demonstrate how the gross costs of environmental programs are affected if regulated firms are compensated for changes in profit induced by an environmental policy. If profits in the regulated sector fall, gross costs increase because the tax on labor must be raised to fund the compensation. In a setting with imperfect capital mobility, Bovenberg et al. (2008) show that a performance standard and technology mandate have relatively small impacts on profit and are therefore preferred to an emissions tax for modest reductions in emissions. The emissions tax reduces profit by raising the cost of all units of emissions, marginal and residual, while the standard and mandate affect profit only through the marginal changes in abatement activities. My work builds on these papers by studying additional instruments, including different configurations of input taxes and restrictions that are relevant for regulating an unobservable source of emissions. I show that with a compensation requirement in place, input taxes may also dominate the emissions tax, and, depending on its design, an input rate restriction may or may not be preferred to an emissions tax.

In addition to exploring the implications of unobservable emissions and distributional concerns for policy instrument choice, a contribution of my work is to examine how the costs of regulating unobservable emissions are affected by the presence of preexisting taxes. The literature on regulating unobservable emissions has largely focused on evaluating the primary costs of policy options and abstracted from interactions with the preexisting tax system.[9] Studies that evaluate the implications of fiscal interactions on environmental policy choice analyze contexts where emissions can be monitored and are based on models that aggregate sectors into single representative firms (for example Goulder et al. (1999)).

[8]The papers most related to my are those that show that the regressivity of a carbon tax depends on how the tax revenues are used to compensate affected groups (Dinan, 2012; Williams et al., 2014).

[9]The notable exception is Fullerton and Wolverton (2005), who derive the optimal two-part instrument for regulating pollution that cannot be taxed directly in the presence of a revenue raising requirement.

GHG Mitigation in the Agricultural Sector

Previous literature on the cost of GHG mitigation in agriculture falls into two broad groups. The first group of studies assess the costs of agricultural mitigation at a 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, highlight the considerable economic potential for mitigation in the agriculture and forestry sectors using a model with a host of mitigation options, including crop, tillage and input intensity choice, biofuels and afforestation. A limitation of these models is that each relies on simplified relationships between management options, yields and emissions. N application rates are constant in De Cara and Jayet (2000) and De Cara et al. (2005), and discrete options in McCarl and Schneider (2001). Moreover, the relationship between activities and emissions are captured using IPCC default methods at an aggregate level, which only partially account heterogeneity in the relationship between N applications and N_2O emissions due to soil and climate characteristics. This heterogeneity of yield and emissions responses to management changes plays a critical role in determining the performance of mitigation policy options.

The second group of studies incorporate data from biophysical models into econometric or economic programming models in order to capture more realistic yield and emissions responses to management changes and heterogeneity in these relationships (Antle and Capalbo, 2001; Antle et al., 2003, 2007; Mérel et al., 2014; Garnache et al., 2014). The integration of biophysical data has proven crucial for estimating the costs of mitigation options. For example, Antle et al. (2003) illustrates that efficiency of per hectare contracts for carbon sequestration, relative to the optimal per ton contract, is negatively correlated to the spatial heterogeneity in production characteristics. A common feature of the linked biophysical and economic models is their focus on small regions or a limited number of management options. Antle and Capalbo (2001) and Antle et al. (2003) focus dryland grain production in Montana, while Antle et al. (2007) focus on two broad cropping systems in the central US. The work by Mérel et al. (2014) and Garnache et al. (2014) focus on the production of seven crops in California's Central Valley.

My work extends the literature on agricultural mitigation along three dimensions. First, I construct a linked general equilibrium and biophysical model at the national level that accounts for heterogeneity in yield and emissions responses at the county level. 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), I analyze a variety of policy options suited to addressing unobservable emissions.[10] Therefore, my results provide more appropriate estimates of the costs of harnessing the mitigation potential of agriculture and offer insights regarding the design of policies for this purpose. Third, unlike each of the prior papers, which assess only primary costs, I assess both primary and gross costs of agricultural mitigation. Chambers (1995) and Parry (1999) illustrate that gross costs may differ drastically from primary costs for agricultural policies, but this insight has yet to be applied to agricultural mitigation.

3 Background

3.1 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 (EPA, 2014).[11] 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 regards to the agricultural sector, 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.[12]

3.2 Agricultural N_2O

The focus of this paper is emissions of nitrous oxide (N_2O) from cropland agriculture, which is the single large source of emissions from agriculture. In the US, cropland N_2O contributes more than half of all GHGs from agriculture and nearly 5% of total GHGs (EPA, 2014).[13] N_2O is a potent GHG that is roughly 300

[10] The exception is Garnache et al. (2014) who study the primary costs of reducing agricultural emissions when an emissions-based policies are unavailable. Relative to this work, I consider a broader set of policies, including acreage taxes and rate input restrictions, and account for preexisting distortions. In addition, my framework is national in scale so heterogeneity in yield and emissions may be of more importance and differentiated policies may be more relevant. Unlike Garnache et al. (2014), I only account for N_2O and do not account for changes in irrigation and tillage intensity.

[11] 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.

[12] 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, Waxman-Markey 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.

[13] A variety of other activities contribute to agricultural GHG emissions. Methane released due to enteric fermentation in ruminant animals, such as cattle, is the second largest source of agricultural GHGs (IPCC, 2014). Changes in soil carbon stocks

times more powerful than CO_2 on a global warming potential basis.[14] Over 70% of agricultural N_2O results from the application of fertilizer to cropland soils (EPA, 2014). 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 cycle.[15] 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). Leguminous crops, such as soybeans, fix atmospheric N into soils, which provides most of the N required by the crop. To sustain growth of non-leguminous crops, and some leguminous crops, N is added to soils, typically in the form of chemical fertilizer or manure (Erisman et al., 2008). However, not all N available in agricultural soils is used by the crop. Excess N in soils leads to a number of environmental problems, including elevated emissions of N_2O.[16] Excess N leads to N_2O directly and indirectly. Direct N_2O emissions 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 to which it was applied in forms other than N_2O, through either volatilization or leaching and runoff, and subsequently converted to N_2O elsewhere.[17] Direct emissions are generally understood to be the major contributor to N_2O, but Turner et al. (2015) suggest that emissions from the leaching and runoff pathway could be substantially larger than previously thought.

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, no studies analyze policy options to reduce agricultural N_2O at a national scale. 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 through changes in soil carbon stocks. 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

due to agricultural activities can be either a source or sink of GHGs (EPA, 2014).

[14]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.

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

[16]In addition to being a greenhouse gas, 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). 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.

[17]Despite fixing atmospheric N, leguminous crops increase atmospheric GHGs. These crops fix atmospheric N_2, which is not a GHG, into soils, thus making N available for conversion to N_2O.

year, a common practice in some regions.[18] 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).[19] Irrigation and tillage are examples of management choices that alter N_2O emission rates by changing soil conditions.

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). 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. 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. Table A.6 displays the heterogeneity across crops and regions in baseline N_2O rates used in my analysis.

Monitoring N_2O Emissions

Due to the nature of the emissions generation process, wide-scale monitoring of 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

[18] 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.

[19] 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 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.

and the temporal distribution of emissions.[20] Measurements from static chambers on cropland is the current economical monitoring option for experimental observation (Hensen et al., 2013). However, using this method at the national scale would be technically impractical and prohibitively costly. 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).

4 Analytical Model

This section presents an analytical model, in the spirit of Goulder et al. (1999) but with heterogeneous firms, that can be used to assess the efficiency costs resulting from a marginal change in policy options to reduce agricultural N_2O. I present formulas that decompose the primary costs of each policy, as well a formula that illustrates the additional costs due to interactions with the distortionary tax system and the compensation requirement. Emissions, input and crop acreage taxes and an input rate restriction are considered in the analytical model. More complicated policy configurations, such as non-uniform input taxes and combinations of policies assessed in the numerical model. The taxes 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.[21] The input rate restriction is an example of a quantity policy, but is more information intensive and difficult to enforce because the regulator must be able to observe input quantities applied to each crop.[22] Information and enforcement costs are not considered in this analysis.

4.1 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 $i = 1 \dots I$. Within each region there are J_i heterogeneous parcels of various sizes, indexed $j = 1 \dots J_i$. The total land area available in each parcel is given by $\bar{A}_{ij}$. Land is combined with intermediate inputs to produce K crops indexed $k = 1 \dots K$. 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.

[20] 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.

[21] 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).

[22] Implementing an input rate restriction would require tracking inputs between purchase and use, monitoring field-level activities or accurate self reporting.

Demand

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

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

where $U(\cdot)$ is the utility from consumption and ϕ is the disutility from emissions. U is continuous, differentiable and strictly quasiconcave 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 endowments and a fixed transfer from the government, G_C:

$$\sum_k P_k C_k + C = \Pi_A + \left(1 - tL\right) L + G_C \tag{2}$$

where P_k is the price of crop k, Π_A is aggregate profit from the land endowment and tL is the labor tax. The consumer chooses C_k, C and L 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 and labor supply functions:

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

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

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

Production

Each parcel of land is independently managed to maximize profits by a risk neutral representative landowner. Productivity and emissions, per unit land, are heterogeneous across crops and parcels. The landowner chooses the quantity of land to allocate to each crop, A_{ijk}, and can influence productivity and emissions using intermediate inputs. Let productivity and emissions per unit land be:[23]

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

where n_{ijk} is the quantity of an intermediate input, N, 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.[24] One can think of y as crop yields, N as nitrogen fertilizer and e as the sum of direct and indirect N_2O emissions per unit land.

Labor used for each parcel's production of crops is made up of two components. The first component is a fixed quantity of labor per unit land allocated to each crop, l_{ijk}, that accounts for all variable inputs other than N. The second component is land management costs that depend on the parcel's land allocation, $L_{ij}\left(A_{ij1},\ldots,A_{ijK}\right)$ and captures factors other than net returns, such as land quality, that induce diversification of crop production within parcels.

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

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

where π_{ijk} is the net returns per unit land to crop k in parcel ij.[25]

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, $\boldsymbol{n}_{ij}\left(P_1\ldots P_K,P_N,P_M\right)$. These functions then determine the total supply of crop k, $Y_k=\sum_{ij} y_{ijk}\left(n_{ijk}\right)A_{ijk}$, total emissions, $E=\sum_{ijk} e_{ijk}\left(n_{ijk}\right)A_{ijk}$, and total labor used for crop production, $L_A=\sum_{ijk} A_{ijk}l_{ijk}+\sum_{ij} L_{ij}$. Total use of the intermediate inputs and total returns to land can be calculated with similar formulas.

Landowners receive a lump sum transfer, G_A, from the government to compensate for any changes

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

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

[25]A limitation of the modeling framework is its treatment of the N application rate decision. The framework does not account for risk preferences, yield or price uncertainty or other behavioral or informational aspects of the input use decision (Stuart et al., 2014). However, there is suggestive evidence that in recent years N is managed at economically optimal rates for the majority of corn acres (Ribaudo et al., 2012).

in aggregate profit due to the environmental program. The size of this transfer is $G_A = \Pi_A^0 - \Pi_A$ where Π_A^0 are aggregate profits to the land endowment prior to the imposition of the environmental policy. In this framework, the transfer does not affect production decisions. Therefore, how the aggregate transfer is distributed amongst landowners has no impact on an instrument's efficiency cost.

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 ($N = L$, $C = L$). This establishes $P_L = P_N = 1$.

Government

The government sets policies to reduce total emissions, funds the transfer to the consumer and compensates producers for any change in profit due to the environmental program. The government's budget is assumed to be balanced. Revenues generated by the environmental policies, therefore, fund reductions in the labor tax.

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:

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

4.2 Primary Cost Decompositions

I start by decomposing primary costs into the channels through which each policy reduces emissions. To isolate primary costs, I set $tL = 0$, neutralize the revenue of the environmental program with a lump sum transfer to the consumer and do not compensate producers for changes in profit. I account for the implications of preexisting taxation and compensation in Section 4.3.

Emissions Tax

If emissions are observable, an emissions tax is available and is the least cost policy. Assume that each landowner is taxed at rate tE for emissions generated by their production activities. The per unit profit functions become $\pi_{ijk} = P_k y_{ijk} - n_{ijk} - l_{ijk} - tEe_{ijk}$. The tax revenue from the policy, and therefore the transfer to the consumer, is $G_C = tEE$.

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

$$-\frac{1}{\lambda_I}\frac{dV}{dtE} = \underbrace{-tE\sum_{ijk} e_{ijk}\frac{dA_{ijk}}{dtE}}_{dW_A} + \underbrace{\sum_{ijk} A_{ijk}\left(P_k y^n_{ijk} - 1\right)\left(-\frac{dn_{ijk}}{dtE}\right)}_{dW_N} \tag{8}$$

where λ_I is the marginal utility of income and $y^n_{ijk} = \frac{\partial y_{ijk}}{\partial n_{ijk}}$. 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 second term, dW_N, is the *input effect.* The input effect is the cost, due to lost profits to the land endowment, resulting from reduced use of the polluting input.

The emissions tax is efficient because the cost of the policy is distributed across both channels of adjustment. The alternative policies are unable to fully utilize each of the channels to reduce emissions, and are therefore more costly.

Uniform Input Tax

Consider a tax on the polluting input, tN. The per unit profit functions are $\pi_{ijk} = P_k y_{ijk} - (1 + tN)\, n_{ijk} - l_{ijk}$ and tax revenue is $G_C = tNN$. The efficiency costs of a marginal increase in the input tax is:

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

The uniform input tax exploits the input effect, but only partially exploits the land allocation effect. The land allocation effect is only partially utilized because the change in crops' per unit profit due to the tax depends on the use of the polluting input rather than the contribution of the input 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 $\pi_{ijh} = P_h y_{ijh} - n_{ijh} - l_{ijh} - tA_h$, and government payments are: $G_C = \sum_{ij} A_{ijh} tA_h$. The efficiency costs of a marginal increase in an acreage tax is:

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

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.[26] 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.

Cost of an Input Rate Restriction

Using "best practice guidelines" to induce changes in management is a frequently recommended strategy to address externalities from agriculture.[27] As an example of this type of approach, I analyze an input rate restriction, which can be thought of as an enforceable upper limit on the application rate of the polluting input. Consider a restrictions on the application rate of the polluting input to a heavily polluting crop, $\bar{n}_h$. Let the set Θ contain all of the parcel/crop combinations for which the input rate restriction binds, $\Theta = \left\{ i \in I, j \in J_i \mid n_{ijh}^* \geq \bar{n}_h \right\}$, where n_{ijh}^* represents the unrestricted optimal application rate. The costs of an incremental change in the input rate restriction, assuming that Θ is unaffected, is:

$$-\frac{1}{\lambda_I}\frac{dV}{d\bar{n}_h} = \underbrace{\sum_{ij \in \Theta} A_{ijh}\left(P_k y_{ijh}^n - 1\right)}_{dW_N}. \tag{11}$$

An input restriction only utilizes the input effect, which is the sum of the change in profit due to a unit reduction in the polluting input for all binding parcels. But, relative to an emissions tax, the input effect is not fully utilized for two reasons. First, all parcels for which the input restriction binds will be affected by the policy in the same manner, as opposed to having a varying effect to account for the variation in marginal productivity and emissions across parcels. Second, the input effect need not be spread across all parcels, since parcels with unrestricted application rates below the maximum level are not required to lower application rates. Unlike an input tax, there is no land allocation effect because an incremental change in the restriction induces only a marginal change in the relative returns to the polluting crop.

The primary cost formulas illustrate the channels through which single, uniform policy instruments reduce emissions. However, the formulas also provide insights about the more complicated policy configurations that will be explored with the numerical model. 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

[26]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.

[27]See Robertson and Vitousek (2009) or Cavigelli et al. (2012) for discussions of the management options.

set in a manner that accounts for heterogeneity in marginal emissions rates across these groups. Likewise, pairing an input tax with acreage taxes will lower primary costs by more fully utilizing the land allocation effect. Input rate restrictions could be improved by extending the restrictions to additional crops. This would spread costs to additional parcels and more fully exploit the input effect.

4.3 Gross Cost Decompositions

To assess gross costs, I allow that labor tax to be positive, fix the government payment to the consumer at a positive value, and require compensation to landowners for lost profit. In what follows, I illustrate the additional cost components due to fiscal interactions for the emissions tax, then discuss how these components would be different for the remaining policies. The gross costs of a marginal change in the emissions tax are:

$$-\frac{1}{\lambda_I}\frac{dV}{dtE} = \underbrace{-tE\frac{dE}{dtE}}_{dW_P} + \underbrace{(1+M)\,tL\left(-\frac{dL}{dtE}\right)}_{dW_{TI}} - \underbrace{M\left(E + tE\frac{dE}{dtE}\right)}_{dW_{RR}} - \underbrace{M\left(\sum_k Y_k \frac{dP_k}{dtE} - E\right)}_{dW_C} \tag{12}$$

where $M = \frac{-tL\frac{\partial L}{\partial tL}}{L + tL\frac{\partial L}{\partial tL}}$ is the typically defined partial equilibrium marginal cost of funds minus one. It is deadweight loss from an increase in the labor tax over revenue generated due by the tax increase. The first term, dW_P are the primary costs of the policy, which can be further decomposed as in the previous section. The second term, dW_{TI}, is the *tax interaction effect*. This effect equals the marginal cost of public funds $(1 + M)$ times the change in labor supply induced by the environmental policy. The environmental policies raise the price of crops which reduces the real wage. This contraction in labor supply generates an efficiency loss due to the prexisting labor tax. This contraction also reduces tax revenue, which must be replaced at cost M. The third term, dW_{RR}, is the *revenue recycling effect*. It is equal to M times the marginal revenue generated by the environmental tax. Each dollar of revenue generated from the environmental tax can replace revenue generated by the labor tax, for a cost savings equal to M.

These three terms are the standard effects emphasized in the literature on environmental taxation with preexisting distortionary taxation. Most studies find that the tax interaction effect easily dominates the revenue recycling effect (Parry, 1995; Goulder et al., 1999). But, the presence of a fixed factor of production, such as land, can cause the revenue recycling effect to dominate the tax interaction effect, and potentially both the primary costs and tax interaction effect (Bento and Jacobsen, 2007). In the presence of a fixed factor, the costs of raising revenue can be lowered as the burden of taxation is shifted away from labor towards the fixed factor. The logic follows from the theory of optimal taxation. In the model, land is a fixed factor of production that generates profits. Since taxing profits is not distortionary, an optimal tax system would fully tax profits. The environmental taxes serve as surrogate profit taxes if profits are not fully taxed.

However, the environmental taxes are distortionary so the cost savings generated by shifting the tax burden from labor to land depends on the marginal excess burden of the environmental tax. This logic also suggests that the marginal excess burden of the environmental taxes will be lowest for instruments that most directly charge land.

The fourth term, dW_C, is the *compensation effect*. It is equal to the marginal change in profit times M. Profit can increase or decrease in response to the environmental policy. If compensation is required, the marginal change in profit is replaced with, or can replace, revenue raised at a net cost equal to M.

The gross costs of the other tax policies can be decomposed with analogous formulas. The gross cost of the input rate restriction differs from equation (A.10). First, the revenue recycling effect disappears because the policy does not generate revenue. Second, the compensation effect no longer includes the quantity of the good being regulated and will be equal to $-M\sum_k Y_k \frac{dP_k}{d\bar{n}_h}$, thus causing the compensation effect to increase. Unlike taxes, which impact profit by raising the cost of all units of a factor of production, marginal and residual, the input rate restrictions only affect profit due to marginal changes in inputs.

5 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. The model takes broadly the same structure as the analytical model, with five 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, land parcels are allowed to vary by irrigation status, an important determinant of yields and emissions rates. Third, a number intermediate sectors are added to better represent the relationship between farm-level decisions that affect crop supply and national-level outcomes. Fourth, additional parameters are included in the agricultural profit equations to rationalize observed N application rates with the biophysical yield data. Finally, profits in the agricultural sector are taxed at the same rate as labor, tL, because both reflect income to the representative consumer.

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 $r \in \{\text{US}, \text{ROW}\}$ 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.

5.1 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. Following Parry (1999), utility is a set of nested constant-elasticity-of-substitution (CES) functions:

$$U = \left(\alpha_U CF^{\rho_U} + (1-\alpha_U)\left(\bar{L}-L\right)^{\rho_U}\right)^{\frac{1}{\rho_U}}$$
$$CF = \left(\alpha_{CF}(F-\bar{F})^{\rho_{CF}} + (1-\alpha_{CF})\, C^{\rho_{CF}}\right)^{\frac{1}{\rho_{CF}}} \tag{13}$$

where ρ_U and ρ_{CF} are functions of the chosen elasticities of substitution, σ_U and σ_{CF}, according to $\rho = \frac{\sigma-1}{\sigma}$, the α terms are calibrated share parameters. The upper nest accounts for the tradeoff between aggregate consumption CF while the lower 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 nest. This is a calibrated parameter that allows the expenditure elasticities for F and C to differ and, if $\bar{F}$ is positive, for C to be a closer substitute for leisure than food.[28] It will also serve to weaken the tax interaction effect (Parry, 1995).

5.2 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 or intensity of irrigation. It is then possible to treat irrigated land and rainfed land in a given county as two separate parcels. For example, Jefferson county Nebraska 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. In the numerical model, I represents groups of states and J represents 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

Yields take the form $y_{ijk} = \hat{y}_{ijk} + \gamma_{ijk} n_{ijk}^{\beta_{ijk}}$ with all parameters, $\hat{y}$, γ and β, positive. This form was chosen so that the calibrated functions could reflect both the marginal yield information from the biophysical model and observed yields. Emissions per unit land, e_{ijk}, are increasing and weakly convex quadratic functions of

[28] 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.

N application rates with crop-parcel specific parameters.

Shadow Costs of N Applications

Similar to Mérel et al. (2014), to ensure that baseline N application rates and the biophysical yield data are consistent with the economic model in equation (6), additional parameters are added to the profit equation to reflect the "shadow costs" of N applications. These shadow costs, ν_{ijk}, drive differences in N application rates across crops and regions that are unrelated to marginal yields by acting as implicit taxes or subsidies on N applications. Therefore, the implicit price of N faced by a given crop-parcel combination is $P_N + \nu_{ijk}$.[29]

Land Allocation

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

$$L_{ij}\left(A_{ij1},\ldots,A_{ijK}\right) = \bar{A}_{ij}\frac{1}{\alpha_i^A}\left(l_{ij} + \sum_k \xi_{ijk}S_{ijk} + \sum_k S_{ijk}\log S_{ijk}\right) \tag{14}$$

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 multinomial logit forms (Carpentier and Letort, 2013):

$$A_{ijl}\left(\pi_{ij1},\ldots,\pi_{ijK}\right) = \bar{A}_{ij}\frac{\exp\left(\alpha_i^A\pi_{ijl} - \xi_{ijl}\right)}{\sum_k \exp\left(\alpha_i^A\pi_{ijk} - \xi_{ijk}\right)}. \tag{15}$$

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

5.3 ROW Demand

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

$$U = \left(\alpha_U C^{\rho_U} + \left(1-\alpha_U\right)F^{\rho_U}\right)^{\frac{1}{\rho_U}} + \frac{{A_U}^{1+\frac{1}{\eta_{A_U}}}}{\gamma_{A_U}\left(1+\eta_{A_U}\right)} \tag{16}$$

[29] The parameters ν_{ijk} are allowed to vary by crop and state. To add shadow costs to the full equilibrium model without adding price distortions, the shadow costs are assumed to be fully captured in the price of N, which is allowed to vary by state and crop. The linear technology parameters of N production are set to reflect these price differences.

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.

5.4 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:

$$X_s^r = \gamma_s^r \left(\sum_q \alpha_{sq}^r {X_{sq}^r}^{\rho_s^r} \right)^{\frac{1}{\rho_s^r}} \tag{17}$$

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 A.1 displays the specific structure of intermediate production.

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

5.5 Market Clearing and Trade

Aggregate demand must equal aggregate supply at the country level for each domestic good, and at the world level for each traded good.

5.6 Solution Method

Given a set of 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 production, market clearing conditions, and zero-profit conditions.[30]

The model is solved as a complementarity problem to account for potential constraints on N application rates due to input rate restrictions. The application rate for each crop-parcel must satisfy the complementarity condition:

$$-\left(P_k \frac{\partial y_{ijk}}{\partial n_{ijk}} - (P_N + \tau_N) - \tau_E \frac{\partial e_{ijk}}{\partial n_{ijk}} \right) \leq 0 \quad \perp \quad n_{ijk} \leq \bar{n}_{ijk} \tag{18}$$

[30] 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.

where $\bar{n}_{ijk}$ is the maximum input rate for each crop-parcel and $\perp$ indicates that if either condition is non-binding, the other condition must be satisfied with equality.[31]

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 associated and $\bar{\Omega}$ be the upper bounds associated with each choice variable. Given policy values, equilibrium is solved by searching for Ω that satisfies:

$$0 \leq \text{EQM}(\Omega; \Phi) \perp \Omega \leq \bar{\Omega}. \tag{19}$$

Optimal Policy Problem

An MPEC formulation is used to compute the optimal policy variables that achieve a targeted 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:

$$\begin{aligned}
&\max_{\Omega,\Phi} \sum_r \theta^r U^r(\Omega; \Phi) \\
&\text{subject to:} \\
&0 \leq \text{EQM}(\Omega; \Phi) \perp \Omega \leq \bar{\Omega} \\
&E(\Omega; \Phi) \leq \bar{E}.
\end{aligned} \tag{20}$$

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

6 Data and Calibration

6.1 Baseline Data

Production and Consumption

Table A.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

[31] Equation (18) is a compact representation of the Karush-Kuhn-Tucker conditions for maximization with an inequality constraint on the input rate.

in each panel reports baseline values of the endowments and crops supplied by each country.[32] The value of each crop 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. 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.

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, 2014b) and Commodity Costs and Returns (ERS, 2014c). Since the model captures long run equilibrium adjustments, the agricultural data used in the model is the average of the available annual data reported by 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 (Table A.2). Counties are included based on the quantity of land allocated to the seven modeled crops. The included counties, mapped in the top panel of Figure A.1 by region, 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 notable ($> 5\%$) share of total land in a county is irrigated. A map of irrigated and rainfed counties is provided in the lower

[32]Since A in the US is used solely by the agricultural sector it is not reported in this table.
[33]Corn and sorghum are harvested for grain. Legume hay is represented by alfalfa.

panel of Figure A.1. 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. See section A.2.2 for additional information about the selection of counties and the construction of crop shares.

The N application rate decisions are not modeled for the legume crops, soybeans and alfalfa, that require little or no mineral N applications. N application rates are fixed at observed baseline levels for soybeans and assumed to be zero for alfalfa.[34] In total, 10,444 crop-county combinations are included in the model, with the N application rate decision modeled in 7,078 crop-county combinations.

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.

6.2 Parameters

US Utility

The US utility functions, equation (13), are calibrated to match key demand elasticities and replicate baseline quantities. First, σ_U and the ratio of the value of leisure to the total value of consumption are set so that the compensated labor supply elasticity is 0.4 and the uncompensated 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).[35]

The baseline labor tax is 0.4, which is roughly the sum of federal and state income, payroll and consumption taxes and is consistent with other studies on the interactions between environmental policies and preexisting taxation (Goulder et al., 1999; Parry, 1999). Given baseline values, the marginal excess burden of the labor tax is just under 0.3.

[34] According to extension sources, applying N to alfalfa is only recommended in special circumstances, such as during establishment or for cold soils.

[35] 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.

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 calibrated to output of the Daycent biogeochemical model (Parton et al., 1998). 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.[36] Critically, Daycent is able to simulate grain and straw yields and N_2O emissions due to N available from, among other sources, synthetic fertilizers, crop residues and asymbiotic fixation, for each crop and management practice represented in the model.

The procedures used to generate yield and emissions response functions from Daycent are laid out in Ogle et al. (2015) and summarized here. Daycent simulations were conducted for a subset of US counties based on county-level data for soil attributes and daily weather. For each county, 1000 simulations were conducted for random combinations of management options. Linear mixed effects models, with logged dependent variables, were used to estimate the relationship between yields and emissions and, site characteristics 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 and irrigation status 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.2. Using the estimated models, yield and emissions response functions are obtained for each county and crop combination using state-level average temperature and county-level data for the moisture index.[37] These response functions are used to generate the data necessary for calibration of the economic model.

The parameters of the variable portion of the yield functions, γ_{ijk} and β_{ijk}, are calibrated based on the relative marginal yields of the estimated response functions at observed regional N application rates and 5% reductions from these rates.[38] Given these parameters, $\hat{y}$ is set to match observed county-level

[36] For example, Daycent simulations underlie the EPA's GHG Inventory (EPA, 2014) estimates of GHG emissions from agricultural soils.

[37] All functions are evaluated with zero organic amendments, 20% residue removal, reduced tillage and a soil sand content of 0.33.

[38] Calibrating to marginal yields at two points allows the yield functions to be consistent with the curvature of the response functions.

yields. Prior to calibration, outlier marginal yield estimates from the response functions are dropped and all marginal yield estimates are scaled so that the average corn yield elasticity with respect to N applications is 0.17. This procedure sets the overall responsiveness of yields to N applications while preserving the relative differences in marginal yields across both parcels and crops. It also allows for the implications of different yield elasticities to be explored. Additional details are provided in section A.3.

The parameters of the emissions functions, e_{ijk}, are chosen to match the emissions response functions over the range of N application rates 25% above and below baseline N application rates, while ensuring the function is increasing and weakly convex.[39]

Shadow Costs of N applications

Given the calibrated yield functions and baseline prices, the shadow costs of N applications, ν_{ijk}, are set so that the model's predicted baseline average N rates match observed baseline N rates for each crop and state. Note, while the baseline dataset only includes crop-state observations of N application rates, N rates will differ by county in the baseline equilibrium. For a given crop, county-level differences in application rates within a state are driven completely by differences in marginal yields. Baseline N application rates by crop and region are reported in Table A.4.

Land Management Costs

Parameters α_i^A in the land management cost function, equation (14),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).[40]

[39] More formally, the emissions response functions are evaluated at 1 kilogram N per hectare increments over the required range. Then, using the generated dataset the parameters of e_{ijk} are solved for with constrained least squares.

[40] 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).

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.

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 ($\sigma = 0.05$).

6.3 Baseline Equilibrium

The baseline allocation of cropland, by region, is displayed in A.3. In total, 100.4 million hectares of land are allocated to the seven crops. Corn and soybeans, at 34.7 and 28.1 million hectares respectively, are the two dominant crops in terms of land area. Production of these crops primarily takes place in the Corn Belt, Lake States and Plains regions, which make up the Midwestern portion of the US. Wheat, grass hay and alfalfa, in that order, are the next three most important crops, although none of these crops is grown on more than 13.5 million hectares. Wheat production takes place predominantly to the west of the Corn Belt in the Plains, Mountains and Southwest regions. Grass hay and alfalfa are distributed more uniformly across regions. Sorghum and cotton each make up a small share of total land at the national scale, but can be relevant in a given region. For example, cotton is the third most important crop in the Southwest in terms of area.

Average N application rates differ widely by crop owing to differences in the marginal productivity of N. National average N application rates for each crop are reported in the bottom row of Table A.4. Per hectare, grass hay and corn are the biggest users of N, with each averaging over 150 kg/ha. Average N application rates for cotton, hay and sorghum are roughly half of those for grass hay and wheat. Applications for the legume crops, soybeans and alfalfa, are small because these crops are able to fix the majority of required N from the atmosphere, additions of N fertilizer have little effect on yield. There is also notable heterogeneity in application rates across regions for each crop. This regional heterogeneity is driven by differences in marginal productivity and typical production practices and farm types (e.g. dairy versus commodity farms). N applications to cropland total 8.7 million tons (Table A.5), which is consistent with ERS (2014a) and FAO (2015) statistics.[41] The vast majority, about 60%, of total N is applied to corn, due to corn's dominant land share and high average N application rate. For similar reasons, grass hay receives the second largest quantity of N, about 22% of total N applied.

Baseline N_2O emissions total 159 $TgCO_2e$ (Table A.7), which is broadly consistent with EPA (2014).[42] N_2O emissions and N_2O emissions rates (Table A.6) are generally associated with crops and regions with the largest N applications. However, the large N_2O emissions attributable to soybean production illustrates the imperfect correlation between N applications and N_2O emissions. Soybeans are the second largest contributor of N_2O after corn, but the second smallest user of N. As a legume, soybeans require little N, if any, N to be applied because the crop fixes atmospheric N. But the N fixed by the crop is then available for conversion to N_2O. This suggests that an N tax will not be a perfect substitute for an emissions tax.

7 Results

7.1 County-level Abatement Costs

Prior to analyzing policies, I calculate partial equilibrium marginal abatement cost curves at the county-level.[43] This analysis allows me to examine how the potential to mitigate N_2O varies across crops, counties and regions. To highlight the within- and across-region heterogeneity in county-level abatement potential I plot the distribution of marginal abatement costs, per hectare, for each region in Figure 1.

In each panel, the thick line illustrates the marginal abatement costs of the median county. To illustrate within-region heterogeneity in abatement costs, the shaded area represents the marginal abatement costs of the central 85% of counties and the thin lines represents the central 50% of counties. The areas of decreasing color intensity represent 5% quantiles on either side of the median. For the median county in the Corn Belt (upper left panel), a 0.1 tCO_2e/ha reduction in N_2O can be achieved for under 15 \$/tCO_2e, and 50% of counties can achieve a reduction of this magnitude for between 10 and 19 \$/tCO_2e.

Figure 2 presents the distribution of county-level marginal abatement costs in the Corn Belt under different assumptions in order to illustrate which factors impact county-level marginal abatement costs.

[41] According to the FAO (2015) between 2007 and 2012, total N use in the US was between 11 and 12 million metric tons. However, this statistic includes uses of N in addition to cropland agriculture. The ERS (2014a) reports that approximately 6.5 million tons of N are applied to corn, soybeans, wheat and cotton, but do not breakdown total N use according to other crops. Baseline N use by these four crops is 6.6 million tons in the model.

[42] The model predicts lower N_2O emissions than reported by EPA (2014), primarily because it does not account for the production of minor crops or manure applications.

[43] To calculate the county-level marginal abatement costs, I fix input and crop prices then solve the agricultural problem (equation (6)) for each county at increments of the emissions tax ranging from 0 to 100 \$/tCO_2e. Plotting the change in emissions, relative to no emissions tax, versus the emissions tax yields the county-level abatement cost curve.

Similar figures can be created, and similar conclusions drawn, for each of the other regions. The first panel on the left displays the distribution of marginal abatement costs under baseline model assumptions (i.e. this panel replicates the upper left most panel in Figure 1). The second panel displays county level marginal abatement costs if the land allocation is fixed at baseline values, thus preventing any mitigation from the land allocation channel. Removing the land allocation channel causes marginal abatement costs to rise across the entire distribution, but only slightly. For a 0.1 tCO_2e/ha reduction, median abatement costs increase by under 1 \$/tCO_2e. The small increase in abatement costs reflects that the vast majority of mitigation occurs as a result of changes in input use, not changes in the land allocation.

Mitigation from the land allocation channel is limited for two reasons. First, since all crops release N_2O, any reduction in emissions due to shifts away from a high emitting crop will be eroded, to some extent, by increased emissions from lower emitting crops. Second, in a given region, lower emitting crops tend to make up smaller shares of the land base (compare Tables A.3 and A.7). Small land shares in the baseline reflect lower returns and historical cropping patterns, which limit the shifting of land into low share crops. This is particularly true in the Corn Belt, where wheat and alfalfa are the lowest emitting crops but each makes up only a tiny fraction of the land allocation in the baseline.

Due to the limited land allocation effect, marginal abatement costs depend almost totally on the cost of achieving emissions reductions by cutting N. The costs of reducing N_2O with cuts in N depend primarily on the relative slopes of the yield and emissions functions, and therefore vary considerably by crop (Table A.8).[44] Across all regions, cuts in N to corn and grass hay reduce emissions far more cheaply than for the other crops, particularly wheat and the legume crops, so counties and regions with larger shares of corn and grass hay will tend to exhibit lower marginal abatement costs.[45] Regional and county-level differences in the slopes of the yield and emissions functions, which reflect the variation in climate and biophysical characteristics capture by the Daycent simulations, also have a substantial impact on the costs of mitigation through cuts in N. Therefore, heterogeneity in county-level abatement costs will depend jointly on the slopes of the yield and emissions function and the land allocation.

The third and fourth panels in Figure 2 illustrate how heterogeneity in land allocation and yield and emissions functions each contribute to the distribution of marginal abatement costs. The third panel displays the distribution of abatement costs when yield and emissions functions for each crop are set to be uniform across counties. The remaining heterogeneity is attributable solely to differences in the baseline land allocation. The reduction in heterogeneity is substantial, a 0.1 tCO_2e/ha, 50% of counties have abatement

[44] For any county ij, the marginal abatement costs of cuts in N to crop k are $\frac{-(P_k y'_k - P_N)}{e'_k}$. Thus, costs will be higher when marginal yields are larger and marginal emissions are smaller.

[45] Since the N application rate choice is not modeled for legume crops, there is no mitigation potential through cuts in N for alfalfa and soybeans.

costs between 10 and 15 $/$tCO_2$e. The rightmost panel displays the distribution of abatement costs when the the land allocation for each county is set to the regional average, therefore isolating the contribution of heterogeneity due to yield and emissions functions, 50% of counties have abatement costs between 9 and 13 $/$tCO_2$e. These final two panels show that the land allocation is a bigger determinant of heterogeneity in marginal abatement costs than heterogeneity in yield and emissions functions, although both factors are important.

Moving back to Figure 1, comparing the abatement costs of the median county in each region illustrates the regional heterogeneity in abatement potential. Flatter curves imply cheaper emissions reductions. Abatement cost curves are shallowest for the Corn Belt, Lake States and South Central regions. The median county in these regions could reduce emissions by 0.1 tCO_2e/ha for between less than 20 $/$tCO_2$e. In contrast, the Northeast, Pacific Northwest and California exhibit much steeper median MAC curves. In the median county of these regions a 0.1 tCO_2e/ha reduction in N_2O would cost in excess of 50 $/$tCO_2$e. The share of land allocated to corn and grass hay relative to wheat is a key driver of the differences in marginal abatement costs across regions. For example, the Corn Belt and Lake States have large shares of land in corn and little land in wheat, which leads to relatively low marginal abatement costs. The Plains have a large share of land in wheat and therefore higher marginal abatement costs.

Within region heterogeneity is most substantial in regions that have larger variation in climate, which affects the yield and emissions functions, and crop mix across counties. The Corn Belt, Lake States and South Central regions have the lowest variance in moisture across counties and relatively homogenous marginal abatement costs. The Pacific Northwest has the highest variance in moisture of any region and extremely heterogeneous marginal abatement costs. As an example of the impact of crop mix, the Plains exhibits significant heterogeneity in county level abatement costs, despite having reasonably uniform distribution of moisture, because the eastern portion of the region contains a number of corn intensive counties, while the rest of the region is wheat intensive.

The significant heterogeneity in county-level abatement costs across regions suggests that policies that cannot account for regional differences in abatement costs will be considerably more costly than policies that can. However, there is also substantial within region heterogeneity in marginal abatement costs suggesting that regionally differentiated policies are unlikely to be efficient.

7.2 Policies Considered

I use the numerical model to evaluate the welfare implications of a range of price and quantity instruments. In addition to the emissions tax (tE) the price instruments considered include a uniform N tax (tN), a non-uniform N tax that varies by region (tN_i), and a combination of the non-uniform N tax and crop-specific acreage taxes ($tN_i + tA_k$).[46] The non-uniform N tax and combination of N taxes and acreage taxes represent common recommendations for improving the efficiency of regulating an unobservable source of emissions (Griffin and Bromley, 1982; Helfand and House, 1995; Fullerton and West, 2002). Input rate restrictions that result in high and low primary costs are also considered. The "high cost" input restriction, $\bar{n}^H$, imposes a maximum N application rate that is uniform across crops and parcels. The "low cost" input restriction, $\bar{n}^L$, imposes a uniform percentage reduction in N application rates on all crops and parcels.[47] Welfare costs, measured as negative equivalent variation, are calculated for a series of decreasing total emissions targets, up to a 10% overall reduction in agricultural N_2O.

The alternative policies are each set to minimize the primary costs of achieving an emissions target, given the available policy instruments. These values are obtained by solving the problem in equation (20). To recover policy values that minimize primary costs, θ^r are set to one for each country, tL is set to zero and all government revenue to be returned to the consumer as a lump sum transfer. These adjustments prevent the environmental policies from being set for terms of trade or revenue raising purposes or to alleviate a preexisting distortion. A summary of the policy values used in the analysis is given in Table 1.

7.3 Primary Costs

To begin the comparison of policy instruments, I present the primary costs of emission reductions for each policy. Comparing primary costs reveal the fundamental differences in how the policies induce mitigation actions to reduce emissions.

Marginal Primary Costs

The marginal primary costs of each policy instrument are plotted for the entire range of emissions reductions in Figure 3 and reported for 5% (7.9 $TgCO_2e$) and 10% (15.9 $TgCO_2e$) reductions in N_2O in the first row of each panel in Table 2.[48] The proceeding rows report the ratio of marginal cost relative to the emissions tax, allowing for a direct comparison of the alternative policy to a first-best policy. Modest cuts in N_2O are achievable at reasonable marginal primary costs. Using an emissions tax, a 5% reduction in N_2O can be

[46] Regionally differentiated policies could create incentives for evasion by transporting taxed goods across borders. However, the tax is differentiated across only 10 broad regions (Figure A.1) so transporting fertilizer from outside a region is unlikely to be cost effective for a vast majority of parcels.

[47] For the high cost restriction, the maximum N rates are set as $\bar{n}_{ijk} = (1-\delta)\max_{i,j,k}(n^0_{ijk})$ where δ is the percent reduction imposed from the maximum of all N rates observed in the baseline (n^0_{ijk}). For the low cost restriction the maximum N rates are set as $\bar{n}_{ijk} = (1-\delta)n^0_{ijk}$.

[48] The marginal costs reported in Figure 3 and Table 2 are approximations based on averages over small changes in the emissions target. As a result, the reported marginal cost will slightly underestimate actual marginal costs. This explains the small difference between the tax rate and primary costs for the emissions tax.

achieved at marginal primary costs of 28 $/tCO$_2$e, which is in line with the social cost of carbon used in US government regulatory impact analyses (Interagency Working Group on Social Cost of Carbon, 2013).[49] Marginal costs increase rapidly with the quantity of emissions reductions. For a doubling in emissions reductions, 5% to 10%, marginal primary costs increase by nearly two and a half times to 72 $/tCO$_2$e.

As suggested by equations (8) to (11), marginal primary costs of each alternative instrument exceed those of the emissions tax. However, the numerical results illustrate that well designed policies can achieve emissions reductions at costs that approach those of a first-best policy. To aid interpretation of the primary cost results, the change in N application rates and the N_2O conversion factor, the percent of N applied that is converted to N in N_2O, relative to the emissions tax are reported in Table 2. The relative change in N application rates indicates how effectively an instrument exploits the input effect, by showing whether a policy over or under induces reductions in N use. The relative change in the N_2O conversion factor indicates how effectively an instrument makes use of the land allocation effect by reallocating land to reduce the emissions impact of N applications.

The uniform tax on N is the most costly tax policy considered and is not close to Pigouvian. At a 5% reduction in emissions, the marginal costs of this instrument are more than 50% greater than the emissions tax. The additional costs are incurred because the tax on N cannot account for differences in yields and 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.

Allowing the N tax to vary across regions drastically reduces primary costs. The non-uniform N tax achieves a 5% reduction at marginal costs only 15% higher than the emissions 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.[50] As a result, the reduction in N use is not nearly as drastic as with the uniform N tax. That the non-uniform tax on N reduces emissions with costs approaching the emissions tax indicates that the much of the heterogeneity in marginal yield and emission rates occurs at a fairly broad spatial scale. However, heterogeneity in emissions rates and yields within broader regions prevent the non-uniform N tax from achieving the first-best outcome. This insight points to a strength of the integrated biophysical and economic framework. Biophysical information at a fine spatial scale is crucial for establishing the relative inefficiency of differentiated policies.

Pairing the non-uniform N taxes with crop-specific acreage taxes further lowers marginal costs. When paired with an N tax the acreage taxes will, to a limited extent, correct the allocation of land by altering

[49] Estimates of the social cost of carbon ranges from 11 to 90 $/tCO$_2$ for 2010 (Interagency Working Group on Social Cost of Carbon, 2013). With a discount rate of 3%, the value is roughly 30 $/tCO$_2$.

[50] The average N tax imposed by the non-uniform tax is lower than the uniform N tax by about 14%. A potential concern is that the differential in N taxes across borders can be large. Tax rates range from 0.08 to 0.27 $/kg, with an average of 0.18 $/kg for a 5% reduction in emissions (Table 1).

the relative returns to crops. This brings the change in N use and the N_2O conversion ratio closer to that of the emissions tax. However, adding the acreage taxes causes only a small reduction in marginal primary costs. For a 5% reduction in emissions, pairing crop-specific acreage taxes with the non-uniform N tax lowers marginal costs to only 11% higher than the emissions tax. These minimal cost savings indicate that the majority of emissions reductions come the input effect as opposed to the land allocation effect.

The high and low cost input rate restrictions achieve the 5% reduction at marginal primary costs of approximately 40 $/tCO_2e$. The marginal primary costs of the input rate restrictions are substantially higher than the emissions tax, and in line with the uniform N tax, because neither policy directly accounts for heterogeneity in marginal emissions or marginal yields.

Marginal primary costs of each of the tax options are increasing, continuous and never cross another tax instrument. Scaling up the taxes induces marginal changes in abatement actions and leads to a smooth evolution of marginal costs. For a doubling in emissions reductions, from 5% to 10%, marginal costs of the tax options increase by slightly under two and a half times.

In contrast, marginal primary costs are discontinuous for the high cost input rate restriction, and fall at these discontinuities.[51] Discontinuities are particularly evident at low emissions reductions targets. Between emissions reductions of 0 and 1 $TgCO_2e$, the marginal primary cost of the high cost input restriction rise to over 25 $/tCO_2e$ then drop to below 10 $/tCO_2e$. By changing the set of farms affected by the regulation, scaling down the input rate restriction can induce non-marginal changes in costs. Since farm-level marginal costs of abatement are not perfectly correlated with N rates, the marginal cost of an input restriction can be discontinuous at points where new farms are affected by the restriction. Marginal costs fall at the discontinuities because the marginal abatement costs are small for the initial units abated by the newly regulated farms. The discontinuities are less noticeable at larger reduction targets because the policy is already binding for the majority of farms. The impact of bringing a small number of new farms under the regulation will be minor relative to the increased costs to previously regulated farms.[52]

Total Primary Costs

Total primary costs of each instrument are reported in Table 2. Total primary costs of an emissions tax are \$111 and \$517 million for a 5% and 10% reduction in N_2O respectively. The ratio of total costs to the emissions tax for each policy are also reported in Table 2 and are plotted for the range of emissions reductions in the top panel of Figure 4.

[51]Marginal primary costs are increasing and continuous for the low cost input restriction because, by construction, this restriction is binding for all crop-parcel combinations.

[52]For a 10% reduction, the restriction binds for 67% of crop-parcel combinations (Table 1), which includes essentially all corn and grass hay acres.

For each of the taxes and the low cost input rate restriction, the total primary cost ratios are nearly identical to the marginal cost ratios, because the marginal costs of these policies increase monotonically. For the same reason, the relative performance of these policies does not change with the level of emissions reductions (as indicated by the approximately horizontal curves for these policies in Figure 4). In contrast, the total primary cost ratio of the high cost input restriction falls rapidly as the number of farms for which the restriction binds increases. As illustrated in Figure 3, the initial reductions due to the high cost restriction are extremely costly relative to the other policies. This causes total primary costs of the high cost restriction to increase rapidly at low levels of reductions and then to remain above each other policy, despite eventually having lower marginal costs than some of the other instruments.

The non-uniform N tax, with and without the acreage taxes, illustrates that policies that regulate easily observable quantities may reduce N_2O emissions with primary costs only slightly higher than a first-best policy. Similar results have been obtained in the context of pollution from agriculture (for example Helfand and House (1995) and Garnache et al. (2014)) and passenger vehicle transportation (Fullerton and Gan, 2005).

7.4 Gross Costs

I focus next on the gross costs of the policies. The goal of this section is to illustrate that fiscal effects can play an important role in determining the relative ranking of policies for mitigation in the agricultural sector and to provide the baseline against which the costs due to the compensation requirement can be isolated. The gross costs of the alternative policies are reported in the first row of each panel in Table 3. The next three rows in each panel decompose the gross costs according to equation (12). The following three rows in each panel display the impact of the policies on key drivers of the components of gross cost, the price of food, which reflects changes in crop prices, and environmental tax revenue.

Gross costs of the alternative policies can be positive or negative. For example, the emissions tax increases welfare by nearly $460 million for a 5% reduction in N_2O, while the uniform N tax reduces welfare by roughly $185 million. Negative gross costs suggest that implementing the environmental policy will increase welfare even before the environmental benefits are considered. The differences in gross costs across policies are driven primarily by the magnitudes of the tax interaction and revenue recycling effects. Consistent with other studies (Parry, 1999; Goulder et al., 1999; Bento and Jacobsen, 2007), the tax interaction effect for all policies is substantially larger than primary costs.[53] However for the tax policies, the revenue recycling effect is of the same magnitude, and can be larger than, the tax interaction effect. At a 5% reduction in

[53]It is worth noting that the magnitude of the tax interaction effect, relative to primary costs, appears particularly amplified in my setting. This only occurs because the emissions reductions targets I simulate, and the resulting primary costs are small.

emissions the tax interaction effect for the emissions tax is roughly 4 times larger than primary costs, but the revenue recycling effect is more than twice as large as the tax interaction effect. It is worth noting again that the relative magnitude of the revenue recycling effect is not unexpected in a model with an under-taxed fixed factor of production (Bento and Jacobsen, 2007). Generally, gross costs will be lower for policies that have smaller impacts on the price of food, due to smaller reductions in N use and crop supply, and that collect more revenue.

Comparing the top and middle panels of 4 illustrates five key points regarding the differences in policy rankings based on primary and gross costs. First, the tax on emissions remains the least cost policy option when gross costs are evaluated. In addition to achieving any emissions reductions with the lowest primary cost, the emissions tax induces a relatively large revenue recycling effect.

Second, the uniform and non-uniform N taxes are substantially more costly than the emissions tax when gross costs are considered as opposed to primary costs. Gross costs of the N taxes are at least twice as large as the costs of the emissions tax, but the primary costs are at most 1.6 times higher. The increased differences in relative costs of the N taxes are due to elevated tax interaction effects due to bigger impacts on N use, and dampened revenue recycling effects because the N taxes generate far less tax revenue than the emissions tax (Table 3).

The environmental tax revenues warrant additional discussion because tax collections are a key determinant of the impact of mitigation policies on agricultural profit. Tax revenue is much larger for the emissions tax than for the uniform and non-uniform N taxes because the emissions function relevant for these policies exhibits returns to scale below one.[54] This 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 to the taxes collected by an emissions tax will be equal the returns to scale of the emissions function. The intuition behind this result is that under an emissions tax each unit of N is implicitly taxed according to its marginal contribution to emissions, but under an N tax all units of N are charged at the same rate. In order to achieve the same level of emissions reductions as an emissions tax, the tax on N must be equal to the tax on emissions times the marginal contribution to emissions of the marginal unit of N. If the emissions function exhibits decreasing returns to scale, the residual units of N will be charged less than they would be under the emissions tax because the marginal unit of N has a smaller marginal contribution to emissions than any residual unit of N. Therefore, total tax revenues will be smaller for the N tax than the emissions tax. Unlike the N taxes alone, tax revenue for the combination of the non-uniform N tax and the acreage taxes is greater than that of the emissions tax because the relevant emissions function exhibits returns to scale greater than

[54] The aggregate emissions function relevant for an N tax treats the land allocation as fixed, $E(\boldsymbol{n}_{ij}) = \sum_{ijk} A_{ijk}(\boldsymbol{n}_{ij}) e_{ijk}(n_{ijk})$, and exhibits returns of to scale of approximately 0.4.

one.[55]

Third, the combination of non-uniform N tax and acreage taxes reduces emissions with nearly the same costs as the emissions tax. The gross cost savings from pairing the acreage tax with the N tax accrue almost solely due to the larger revenue recycling effect. In contrast to N taxes alone, the relative costs of the tax combination falls dramatically when gross costs are considered. This occurs because the acreage tax is nearly a perfect replacement for a non-distortionary profit tax and generates a large revenue recycling effect.

Fourth, due to the lack of a direct revenue recycling effect, the input rate restrictions are the most expensive policies in terms of gross costs.[56] Both restrictions reduce emissions at gross costs exceeding those of the emissions tax by at least 2.75 times, and upwards of 3 times for larger emissions reductions. When evaluated based on gross costs, the low cost input restriction is no longer comparable to the uniform N tax. The lack of a direct revenue recycling effect may be another reason, in addition to comparatively high primary costs and implementation difficulties, to favor price instruments over quantity restrictions for addressing unobservable sources of emissions.[57] A secondary point is that the high cost input restriction has lower gross costs than the low cost restriction, due to a smaller tax interaction effect. The high cost restriction has a relatively small impact on the price of food because it regulates only the highest N users.

Fifth, unlike primary costs, gross costs of the alternative policies strongly diverge from those of the emissions tax for larger reduction targets. For example, the costs of a uniform N tax rise from double to triple those of the emissions tax between a 5% and 10% reduction in N_2O. The divergence in gross costs is driven by a contraction of the revenue recycling effect, relative to the emissions tax. The tax base for the N taxes fall faster than the base for the emissions tax, lowering the efficiency benefit of shifting the burden of revenue raising to the N taxes. A similar pattern emerges for the combination of the non-uniform N tax and the acreage tax, but it is much more limited because land in agricultural production makes up a portion of the tax base. The input restrictions raise revenue only indirectly by raising profit to the agricultural sector, but the contraction of the revenue recycling effect occurs because the efficiency costs associated with raising profit by a unit increases for larger reductions in emissions.[58]

The partial equilibrium models, such as (McCarl and Schneider, 2001; Garnache et al., 2014), typically used to assess agricultural mitigation options must focus solely on primary costs and as a result may misrepresent, in either direction, the inefficiency of instruments that do not directly regulate emissions. My

[55]When acreage taxes are considered, the emissions function must treat the land allocation as an input to emissions and returns to scale are greater than one.

[56]The revenue recycling effect is negative, but smaller than the tax interaction effect, for the input restrictions because these instruments only raise revenue through increased tax collections on agricultural profits.

[57]This result is in line with results from the double-dividend literature that illustrates the dominance of an emissions tax over emissions quotas with grandfathering (Goulder et al., 1999).

[58]Note that for a 5% reduction in emissions, the average efficiency lost per dollar of increased profit is 0.03 and 0.04 for the low and high cost input restrictions respectively. For a 10% reduction, the efficiency losses are 0.07 and 0.06.

results show that the difference in relative efficiency is larger for the N taxes and input rate restrictions, but smaller for the N and acreage tax combination.

7.5 Gross Costs with Compensation

The results presented thus far have not accounted for the impact of the policies on profit in the agricultural sector. I find that agricultural profits actually increase due to each of the mitigation policies (Table 4). Although the mitigation policies lower profit due to tax payments and mitigation actions undertaken, these losses are offset by increased revenue due to elevated crop prices (compare the crop supply and inputs rows to the crop prices row in Table 4). That most of the costs of mitigation are pushed onto consumers through elevated crop prices is a consequence of food demand being relatively inelastic. The increases in profit, however, differ dramatically across policies. Profit impacts are largest for policies that have a larger impact on N use, crop supply and therefore crop prices, and for policies that require smaller tax payments. Profit increases by only 3.7 $/ha under the emissions tax, due to its large tax burden, but much more under the uniform tax on N (42 $/ha) and the low cost input restriction (63 $/ha).

To compare policy instruments after accounting for the impacts on profit, I focus on the relative differences in gross costs with the compensation requirement imposed (displayed in the lower panel of figure 4).[59] Imposing the compensation requirement dramatically alters the policy rankings. The tax on emissions is no longer always the low cost policy. In fact, for a 5% reduction in emissions all policies except the non-uniform N tax and high cost input restriction are cheaper than the emissions tax. With the compensation requirement in place, the most cost effective policy is the low cost input restriction, which is 24% less costly than the emissions tax. This policy causes the largest increase in agricultural profit, which with compensation in place outweighs its high gross costs. The uniform N taxes and the combination of N and acreage taxes are slightly more expensive, at 6% and 7% less costly than the emissions tax. That an input restriction dominates the emissions tax is in line with (Bovenberg et al., 2008), but that input taxes may also dominate the emissions tax is a new result.

The most costly policy is the high cost input rate restriction (17% higher than the emissions tax), because the change in profit it induces, while larger than all of the tax policies, is small relative to its gross costs. That the two input rate restrictions bound the tax policies demonstrates that the design of input rate restrictions is critical when balancing efficiency and distributional concerns. The advantages in terms of profit impacts of the input restrictions are not necessarily sufficient to offset the high gross costs of these

[59]Since profits increase under each policy, imposing compensation lowers the cost of the environmental regulation because transfers from the agricultural sector replace revenue raised by distortionary taxation. These costs are displayed in the final rows of each panel in Table 3

policies.[60]

The relative dominance of the tax policies and the low cost restriction over the emissions tax deteriorates with larger reductions in emissions. This reflects the divergence in gross costs (without compensation) between these policies and the emissions tax. The larger gross costs can eventually overwhelm the compensation effect. This trend is particularly notable for the uniform and non-uniform N taxes. Both policies become more expensive than the emissions tax for reasonable reductions in emissions. The costs of the non-uniform tax on N surpass those of the emissions tax after approximately 7 $TgCO_2e$ of emissions reduced. The uniform tax on N will only dominate the emissions tax prior to 12.5 $TgCO_2e$ reduced. In contrast, the dominance of the combination of the non-uniform N tax and the acreage taxes drops only slightly because its gross costs (without compensation) are nearly identical to those of the emissions tax. Over the range of emissions I study, the low cost mandate always dominates each of the other policies because the profit advantages are large enough to outweigh the large and growing differences in gross costs. However, the upward slope of the low cost restriction's gross cost ratio curve suggest that for some level of emissions reductions the low cost restriction may no longer be the preferred policy.

The tension between efficiency and distributional concerns complicates general advice regarding policy instrument choice in the presence of unobservable emissions. With the compensation requirement imposed, strategies suggested for lowering the costs of reducing an unobservable source of emissions may increase or decrease gross costs. Moving from the uniform to the non-uniform N tax, or to the combination of non-uniform N tax and crop acreage taxes, substantially reduces primary costs but also lessens the impact on crop prices and profits. If compensation is in place, the smaller increase in profit dominates and the uniform tax on N is the lowest cost of the tax policies. In contrast, moving from the high cost to the low cost input rate restriction lowers both primary costs and gross costs with compensation.

7.6 Sensitivity Analysis

To test whether the policy instrument rankings are robust to underlying assumptions, I run the same simulations described in the previous section under parameter assumptions that generate low and high cases for the crop area elasticities, yield elasticities with respect to N application rates, food demand elasticities and the elasticity of labor supply. Table 5 displays the sensitivity of the costs of emissions reductions to these cases. The three panels display results for primary costs, gross costs and gross costs with compensation for a 5% reduction in emissions. The first column of numbers displays the costs of an emissions tax. The remaining columns report the ratio of costs to the emissions tax for each of the other policies. The top row in each

[60] It is worth noting that the quantity restrictions analyzed here are relatively inflexible since uniform percent reductions are imposed from the established baseline rates. Allowing the percent reductions to vary, across regions or crops, will result in more efficient input restrictions.

panel reports the costs and cost ratios under the central parameter assumptions. The impacts the alternative parameter assumptions on other key variables, the price of food, tax revenue from the environmental policies and agricultural profit are presented in Table 6. Sensitivity results for a 10% reduction are presented in Tables A.10 and A.11.

The parameter assumptions greatly affect the total primary and gross costs of the policies, but have little effect on the costs of alternative policies relative to the emissions tax and no effect on policy rankings. As such, the sections below primarily focus on how the parameter assumptions affect the costs of the emissions tax, and refer to the other policies when notable changes in relative costs occur.

Crop Area Elasticities

Raising parameters α_i^A in equation (14) increases the elasticities of crop area with respect to crop returns (η_A). To generate high and low cases for the area elasticities, α_i^A are set so that the baseline national area elasticity of corn is 50% above and below the central value.[61] Higher crop area elasticities imply lower primary costs for the emissions tax because the land allocation effect is easier to exploit (Table 5). The uniform and non-uniform N taxes, which partially exploit the land allocation effect and input rate restrictions, which do not exploit the land allocation effect, have relatively higher primary costs than the emissions tax, because raising the area elasticities causes the land allocation effect to grow in importance relative to the input effect. Raising the area elasticities increases the gross costs the emissions tax, with or without the compensation requirement, because the revenue recycling effect is weakened as the emissions supply becomes more elastic.

Yield Elasticities

Sensitivity of results to yield elasticities are explored by calibrating the yield functions so that the national corn yield elasticity with respect to N rates is 20% above and below the central value, while maintaining the relative differences in marginal yields across parcels and crops from the biophysical model. Larger yield elasticities imply higher marginal costs of abatement at the farm level, and larger costs of emissions reductions for all policies, as cutting N applications leads to bigger drops in crop yields. The increase in cost can be drastic, a 20% increase in the overall yield elasticity level increases primary costs of the emissions tax by about 30%. The costs of the alternative policies increase relative to the emissions tax, with the exception of the high-cost restriction, because over exploiting cuts in N to reduce emissions has bigger impacts on crop production. More elastic yields cause the high cost restriction to become less costly relative to the emissions tax, because yields are directly affected for only a subset of parcels and crops. Gross costs of the emissions

[61] For each set of α_i^A, the parameters ξ_{ijk} and l_{ij} are recalculated so that predicted crop shares match observed crop shares and management costs are zero in the baseline.

tax fall dramatically with increases in yield elasticities. The larger tax interaction effect, which results from a larger increase in the food price, is dominated by a larger revenue recycling effect due to the larger emissions tax required to achieve the same reduction in emissions.

Food Demand Elasticities

Parameters σ_{CF}^{US} and σ_{U}^{ROW} alter food demand elasticities by changing consumers' ability to substitute between food and other consumption. The high and low food demand elasticity cases set these two parameters so that the uncompensated food demand elasticities are 50% above and below central values. These demand elasticities partially control the elasticity of crop demand and therefore the impact of mitigation policies on crop prices. Raising the food demand elasticities lowers primary costs of emissions reductions of all policies because reductions in crop supply induce smaller increases in the price of crops and food. Raising the food demand elasticities causes the primary costs of the emissions tax to fall slightly from 111 to 109 $/$CO_2$e and the primary costs of the remaining policies to fall almost proportionately (Table 5).[62] Gross costs of the emissions tax are almost constant as food demand elasticities are increased because the tax interaction and revenue recycling effects both fall due to the smaller required tax on emissions. With the compensation requirement in place however, gross costs of the emissions tax increase with the food demand elasticities because the rise in crop prices, and thus agricultural profit, is softened.

Labor Supply Elasticities

The compensated and uncompensated labor supply elasticities (denoted η_L) are raised and lowered by 20% from the central values by recalibrating σ_U and $\bar{L}$ in equation (13). Raising the elasticity of labor supply increases the marginal excess burden of the labor tax, thereby increasing the benefits of using revenue from the environmental policies to lower the labor tax. As shown in Table 5 the labor supply elasticity has no impact on primary costs of the emissions tax, but gross costs and gross costs with compensation fall dramatically. The fall in gross costs with compensation is larger because the larger reduction in the labor tax is amplified due to the higher marginal excess burden.

8 Conclusion

This paper used analytical and numerical general equilibrium models to explore policy options to reduce GHG in sectors that are exempt from climate change legislation. I focus on two constraints that preclude a

[62]Primary costs of the alternative policies actually fall by more than the emissions tax, because the larger than necessary cuts in N, and therefore crop supply, have a smaller impact on food prices. This differential effect becomes more perceptible at larger emissions reductions (Table A.10).

sector from inclusion in climate legislation and prevent first-best policies from being used in these sectors: unobservable emissions and distributional concerns regarding profit of regulated firms. When jointly considered these constraints greatly affect the policy instrument choice decision; policy options suggested for reducing the costs of addressing an unobservable source of emissions can have more prominent impact on firm profit. If a compensation requirement is imposed to formalize the distributional concerns, input-based policies can be the least cost policy options even if an emissions tax is available.

My numerical application provides national-scale cost estimates for reducing agricultural N_2O using a variety policy options. Like previous studies on the regulation of unobservable emissions, I find that alternative policies based on observable inputs can achieve emissions reductions with primary costs approaching those of first-best policy. However, I show that when accounting for gross costs, which incorporate costs due to interactions with the fiscal system, input-based policies tend not to be comparable to an emissions tax, but this depends on the particular inputs being regulated.

Two limitations of my analysis deserve attention. First, the model includes a limited set of agricultural management practices and considers only N_2O emission. As previously mentioned, other management practices, such as placement, timing and type of N fertilizer applications and tillage and irrigation intensity will, under certain conditions, affect N_2O emission rates (Eagle et al., 2012). Further, changes in agricultural production practices will also affect other sources of emissions and mitigation, notably the uptake and sequestration of atmospheric carbon into soils (EPA, 2014). Incorporating these additional mitigation channels would lower the primary costs of mitigation and would widen the gap between an emissions tax and alternative polices, since each channel would need to be controlled to efficiently regulate emissions.

Second, I focus on a single distributional concern, the policy impact on the aggregate profit of the agricultural sector. This is one of many distributional issues underlying agri-environmental policy choice. Perhaps most notably, is the tradeoff between agricultural profit and consumer welfare mediated through the price of food. My analysis illustrates this tradeoff in broad sense, showing that imposing compensation requirements justifies policies that induce larger increases in the prices of crops and food. But, to fully understand the distributional impacts it would be necessary to assess the impacts of elevated food prices on groups for which the impacts would be severe, such as low income households or food importing countries and on other outcomes, such as the frequency of civil conflicts (Bellemare, 2015). A further distributional issue is regional differences in the impact of mitigation policies, particularly for the non-uniform policies. Although not presented here, my framework provides agricultural results at the county level that could be used to highlight the regional impacts of agricultural mitigation policies.

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Table 1: Values Policy Instruments

	tE	tN	tN_i	$tN_i + tA_k$	$\bar{n}^H$	$\bar{n}^L$
7.9 $TgCO_2e$ Reduction						
tE, (\$/tCO_2e)	30.10					
tN average, (\$/kg)		0.21	0.18	0.18		
min		0.21	8	8		
max		0.21	0.27	0.27		
tA average, (\$/ha)				32.69		
Corn				26.47		
W. Wheat				23.21		
Soybean				41.02		
$\bar{n}$ average, (kg/ha)					129.50	107.60
Corn					129.50	126.28
W. Wheat					129.50	51.94
Grass Hay					129.50	134.47
Fraction of Parcels Regulated	1.00	1.00	1.00	1.00	0.58	1.00
15.9 $TgCO_2e$ Reduction						
tE, (\$/tCO_2e)	75.11					
tN average, (\$/kg)		0.53	0.45	0.44		
min		0.53	0.20	0.20		
max		0.53	0.67	0.65		
tA average, (\$/ha)				81.72		
Corn				69.72		
W. Wheat				56.61		
Soybean				100.73		
$\bar{n}$ average, (kg/ha)					97.93	84.17
Corn					97.93	98.74
W. Wheat					97.93	40.61
Grass Hay					97.93	105.15
Fraction of Parcels Regulated	1.00	1.00	1.00	1.00	0.67	1.00

Table 2: Primary Costs of Alternative Policies

	tE	tN	tN_i	$tN_i + tA_k$	$\bar{n}^H$	$\bar{n}^L$
7.9 $\mathbf{TgCO_2e}$ Reduction						
Marginal ($/$tCO_2e$)	28.29	42.82	32.44	31.31	39.52	43.31
ratio to t_E	1.00	1.51	1.15	1.11	1.40	1.53
Total (million $)	111.16	173.94	127.70	123.69	202.14	172.88
ratio to t_E	1.00	1.56	1.15	1.11	1.82	1.56
Δ N Use (ratio to t_E)	1.00	1.56	1.17	1.12	1.03	1.24
% N to N_2O-N (ratio to t_E)	1.00	1.10	1.03	1.02	1.00	1.04
15.9 $\mathbf{TgCO_2e}$ Reduction						
Marginal ($/$tCO_2e$)	72.40	98.84	83.32	79.15	97.22	107.33
ratio to t_E	1.00	1.37	1.15	1.09	1.34	1.48
Total (million $)	517.81	749.64	594.56	570.19	750.19	781.68
ratio to t_E	1.00	1.45	1.15	1.10	1.45	1.51
Δ N Use (ratio to t_E)	1.00	1.45	1.18	1.12	1.09	1.24
% N to N_2O-N (ratio to t_E)	1.00	1.20	1.07	1.05	1.03	1.09

Table 3: Gross Costs of Alternative Policies

	tE	tN	tN_i	$tN_i + tA_k$	$\bar{n}^H$	$\bar{n}^L$
7.9 $TgCO_2e$ Reduction						
Gross Costs (million $)	-461.47	185.06	135.21	-447.50	404.45	461.17
Primary Cost	111.16	173.94	127.70	123.69	202.14	172.88
Tax Interaction	439.50	507.15	454.42	468.97	399.84	567.47
Revenue Recycling	-1012.13	-496.02	-446.91	-1040.16	-197.52	-279.17
Gross Costs (ratio to t_E)	1.00	2.40	2.29	1.03	2.88	3.00
Δ P_F (%)	0.78	0.89	0.80	0.83	0.83	0.99
Δ Env. Taxes ($/ha)	45.43	14.31	13.25	45.83	0.00	0.00
Δ Labor Tax (%)	-0.11	-0.06	-0.05	-0.12	-0.02	-0.03
Gross Costs, w/Comp (million $)	-529.89	-562.52	-527.04	-567.08	-439.36	-656.08
ratio to t_E	1.00	0.94	1.01	0.93	1.17	0.76
Δ Ag. Profit ($/ha)	3.86	42.07	37.30	6.75	47.45	62.77
Compensation Effect	-68.42	-747.58	-662.24	-119.57	-843.81	-1117.25
15.9 $TgCO_2e$ Reduction						
Gross Costs (million $)	-878.12	833.08	657.71	-812.64	1215.56	1373.87
Primary Cost	517.81	749.64	594.56	570.19	750.19	781.68
Tax Interaction	955.42	1088.79	980.99	1016.37	903.63	1165.80
Revenue Recycling	-2351.35	-1005.34	-917.84	-2399.20	-438.26	-573.61
Gross Costs (ratio to t_E)	1.00	2.95	2.75	1.07	3.38	3.56
Δ P_F (%)	1.77	1.99	1.80	1.89	1.91	2.14
Δ Env. Taxes ($/ha)	107.48	27.64	25.94	107.63	0.00	0.00
Δ Labor Tax (%)	-0.27	-0.11	-0.10	-0.27	-0.05	-0.06
Gross Costs, w/Comp (million $)	-904.80	-855.12	-848.55	-959.48	-700.05	-964.44
ratio to t_E	1.00	1.05	1.06	0.94	1.23	0.93
Δ Ag. Profit ($/ha)	1.51	94.96	84.75	8.32	107.57	131.16
Compensation Effect	-26.68	-1688.21	-1506.25	-146.83	-1915.61	-2338.31

Table 4: Impact of Alternative Policies on Agricultural Profit

	tE	tN	tN_i	$tN_i + tA_k$	$\bar{n}^H$	$\bar{n}^L$
7.9 $\mathbf{TgCO_2e}$ Reduction						
Δ Profit ($/ha)	3.86	42.07	37.30	6.75	47.45	62.77
tax payments	-45.43	-14.31	-13.25	-45.83	0.00	0.00
Δ crop supply	-20.93	-24.54	-21.85	-22.36	-21.42	-27.27
Δ inputs	19.31	22.12	20.03	20.57	18.71	24.70
Δ crop prices	50.90	58.81	52.37	54.37	50.16	65.34
15.9 $\mathbf{TgCO_2e}$ Reduction						
Δ Profit ($/ha)	1.51	94.96	84.75	8.32	107.57	131.16
tax payments	-107.48	-27.64	-25.94	-107.63	0.00	0.00
Δ crop supply	-49.96	-58.38	-52.02	-53.41	-53.23	-62.91
Δ inputs	42.03	47.18	43.11	44.65	41.90	50.74
Δ crop prices	116.92	133.79	119.61	124.70	118.90	143.33

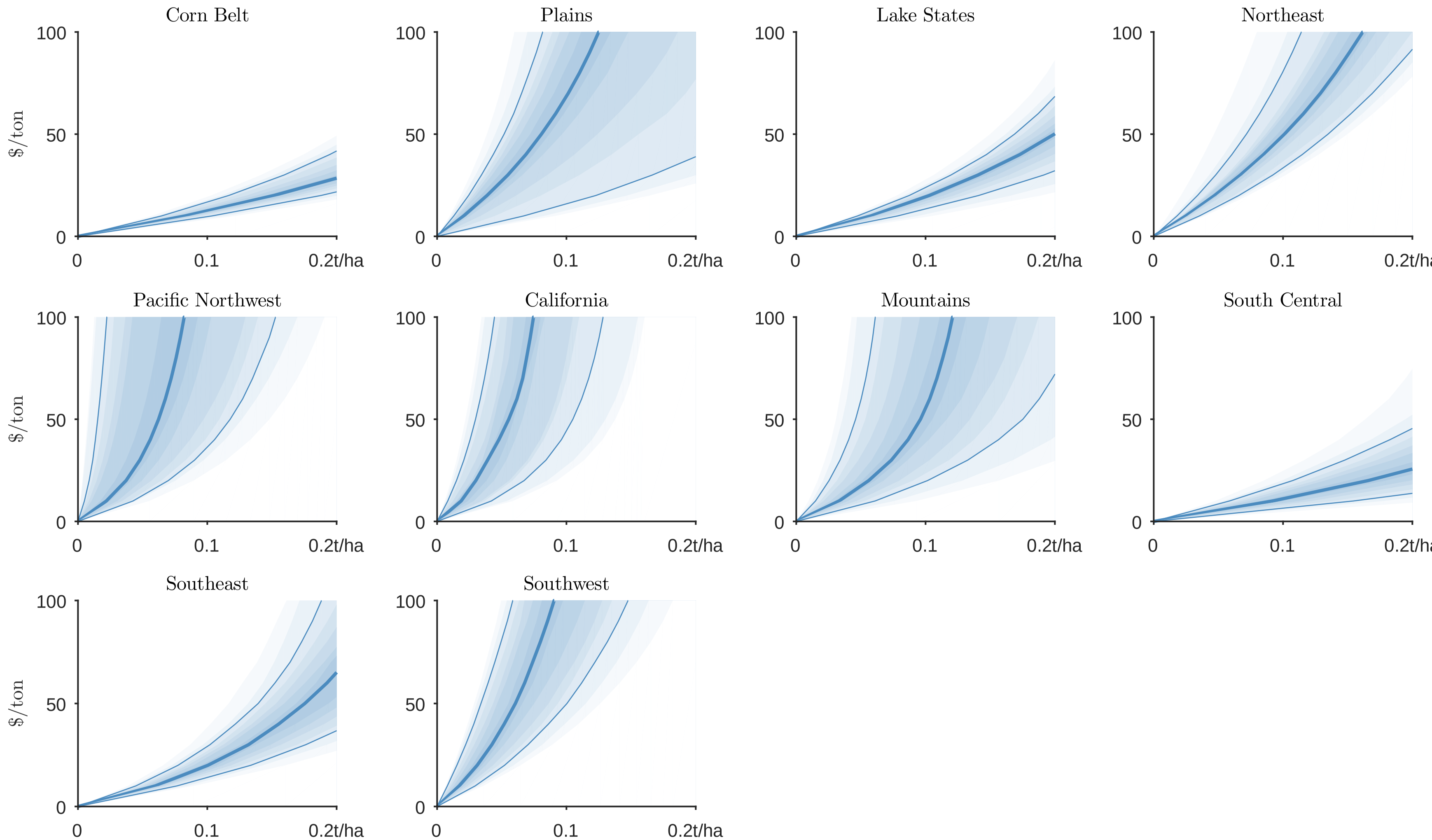
Table 5: Policy Costs Under Alternative Parameter Assumptions (5% Reduction)

	tE million \$	tN	tN_i	$tN_i + tA_k$	$\bar{n}^H$	$\bar{n}^L$
		Ratio to tE				
Primary Costs						
Central	111.16	1.56	1.15	1.11	1.82	1.56
Low η_A	115.02	1.55	1.13	1.11	1.76	1.49
High η_A	108.33	1.58	1.16	1.11	1.87	1.61
Low η_Y	80.13	1.50	1.13	1.10	1.83	1.50
High η_Y	144.96	1.63	1.17	1.12	1.76	1.61
Low η_F	113.22	1.58	1.15	1.11	1.82	1.57
High η_F	109.30	1.55	1.15	1.11	1.82	1.55
Low η_L	111.19	1.56	1.15	1.11	1.82	1.56
High η_L	111.13	1.56	1.15	1.11	1.82	1.56
Gross Costs						
Central	-461.47	2.40	2.29	1.03	2.88	3.00
Low η_A	-475.47	2.40	2.30	1.03	2.87	2.99
High η_A	-451.99	2.40	2.29	1.03	2.89	3.01
Low η_Y	-309.80	2.49	2.38	1.05	2.99	3.12
High η_Y	-634.98	2.34	2.23	1.02	2.79	2.92
Low η_F	-465.12	2.42	2.31	1.03	2.90	3.03
High η_F	-458.12	2.38	2.28	1.03	2.85	2.97
Low η_L	-337.14	2.54	2.40	1.04	3.07	3.18
High η_L	-591.32	2.32	2.23	1.02	2.76	2.89
Gross Costs with Compensation						
Central	-529.89	0.94	1.01	0.93	1.17	0.76
Low η_A	-543.34	0.90	0.97	0.93	1.13	0.72
High η_A	-516.70	0.97	1.04	0.93	1.20	0.80
Low η_Y	-436.10	0.94	1.01	0.94	1.17	0.78
High η_Y	-614.17	0.94	1.00	0.92	1.17	0.75
Low η_F	-556.96	0.93	1.00	0.93	1.16	0.76
High η_F	-505.43	0.94	1.01	0.93	1.18	0.77
Low η_L	-390.38	0.97	1.01	0.93	1.23	0.78
High η_L	-675.80	0.92	1.00	0.93	1.13	0.75

Table 6: Policy Impacts Under Alternative Parameter Assumptions (5% Reduction)

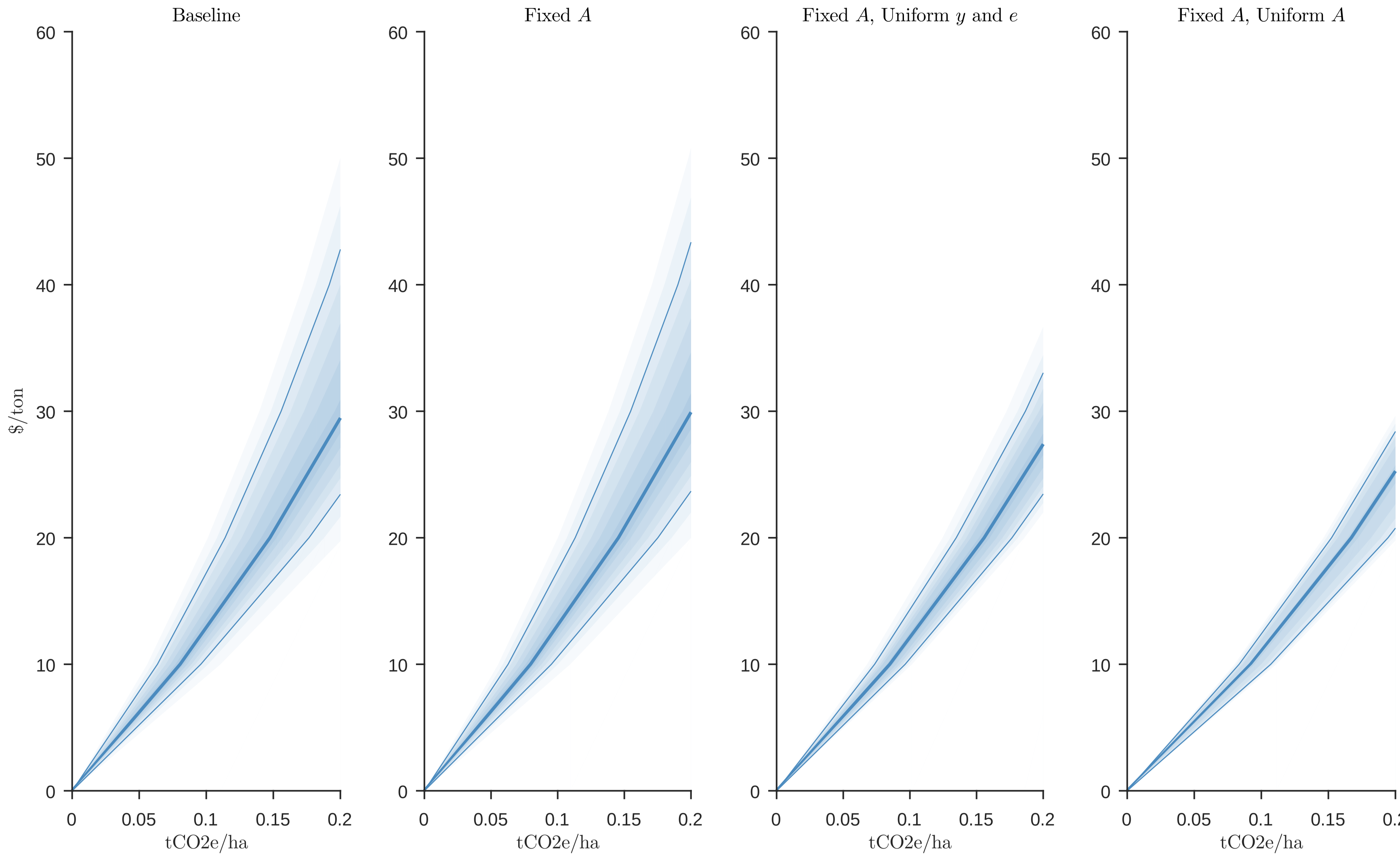
	tE	tN	tN_i	$tN_i + tA_k$	$\bar{n}^H$	$\bar{n}^L$
ΔP_F						
	%	Ratio to tE				
Central	0.77	1.14	1.03	1.07	1.07	1.27
Low η_A	0.80	1.17	1.05	1.08	1.10	1.29
High η_A	0.75	1.13	1.01	1.07	1.05	1.26
Low η_Y	0.62	1.13	1.02	1.07	1.06	1.25
High η_Y	0.92	1.17	1.04	1.08	1.07	1.30
Low η_F	0.81	1.15	1.03	1.07	1.07	1.28
High η_F	0.74	1.14	1.03	1.07	1.07	1.27
Low η_L	0.78	1.14	1.03	1.07	1.07	1.27
High η_L	0.77	1.14	1.03	1.07	1.07	1.27
Δ Env. Taxes						
	$/ha	Ratio to tE				
Central	45.32	0.32	0.29	1.01	0.00	0.00
Low η_A	46.98	0.31	0.29	1.01	0.00	0.00
High η_A	44.11	0.32	0.29	1.01	0.00	0.00
Low η_Y	32.54	0.31	0.29	1.00	0.00	0.00
High η_Y	59.28	0.32	0.30	1.02	0.00	0.00
Low η_F	46.20	0.32	0.29	1.01	0.00	0.00
High η_F	44.52	0.32	0.29	1.01	0.00	0.00
Low η_L	45.33	0.32	0.29	1.01	0.00	0.00
High η_L	45.31	0.32	0.29	1.01	0.00	0.00
Δ Ag. Profit						
	$/ha	Ratio to tE				
Central	3.68	11.41	10.12	1.79	12.90	17.08
Low η_A	3.64	12.18	10.84	1.81	13.65	18.07
High η_A	3.48	11.50	10.17	1.81	13.12	17.38
Low η_Y	6.98	4.96	4.45	1.35	5.41	7.10
High η_Y	-1.37	-35.61	-31.17	-1.33	-41.43	-55.60
Low η_F	4.99	8.89	7.87	1.62	9.99	13.22
High η_F	2.50	15.94	14.17	2.08	18.11	24.03
Low η_L	3.70	11.37	10.09	1.78	12.85	17.02
High η_L	3.67	11.45	10.16	1.79	12.94	17.14

Figure 1: Distribution of County-level Marginal Abatement Costs Within and Across Regions



Notes: Thick line in each panel represents marginal abatement cost of median county. The shaded area represents the central 85% of counties. Shading intensity descends at 5% quantiles on either side of the median. Thin lines denote central 50% of counties.

Figure 2: County-level Marginal Abatement Costs Within Cornbelt, Under Various Assumptions



Notes: Thick line represents partial equilibrium marginal abatement cost of median county. The shaded area represents the central 85% of counties. Shading intensity descends at 5% quantiles on either side of the median. Thin lines denote central 50% of counties. First panel on left displays marginal abatement costs. Remaining panels display marginal abatement costs under various assumptions: Fixed A - land allocation is fixed at baseline values; Uniform y and e - for each crop, yield and emission functions from county with median N application in region are assigned to each other county; Uniform A - land allocation set to region average in all counties.

Figure 3: Marginal Primary Costs of Alternative Policies

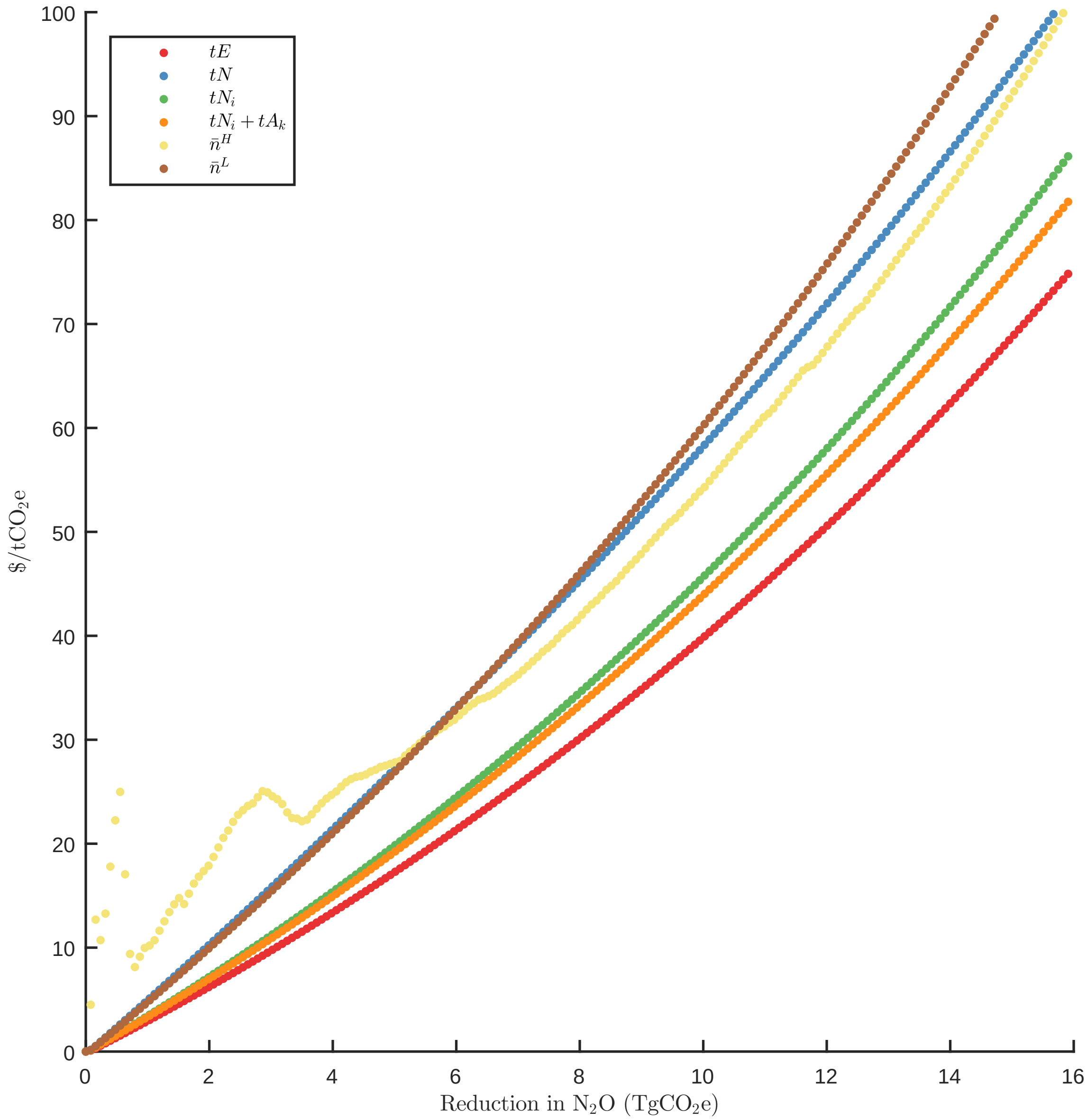
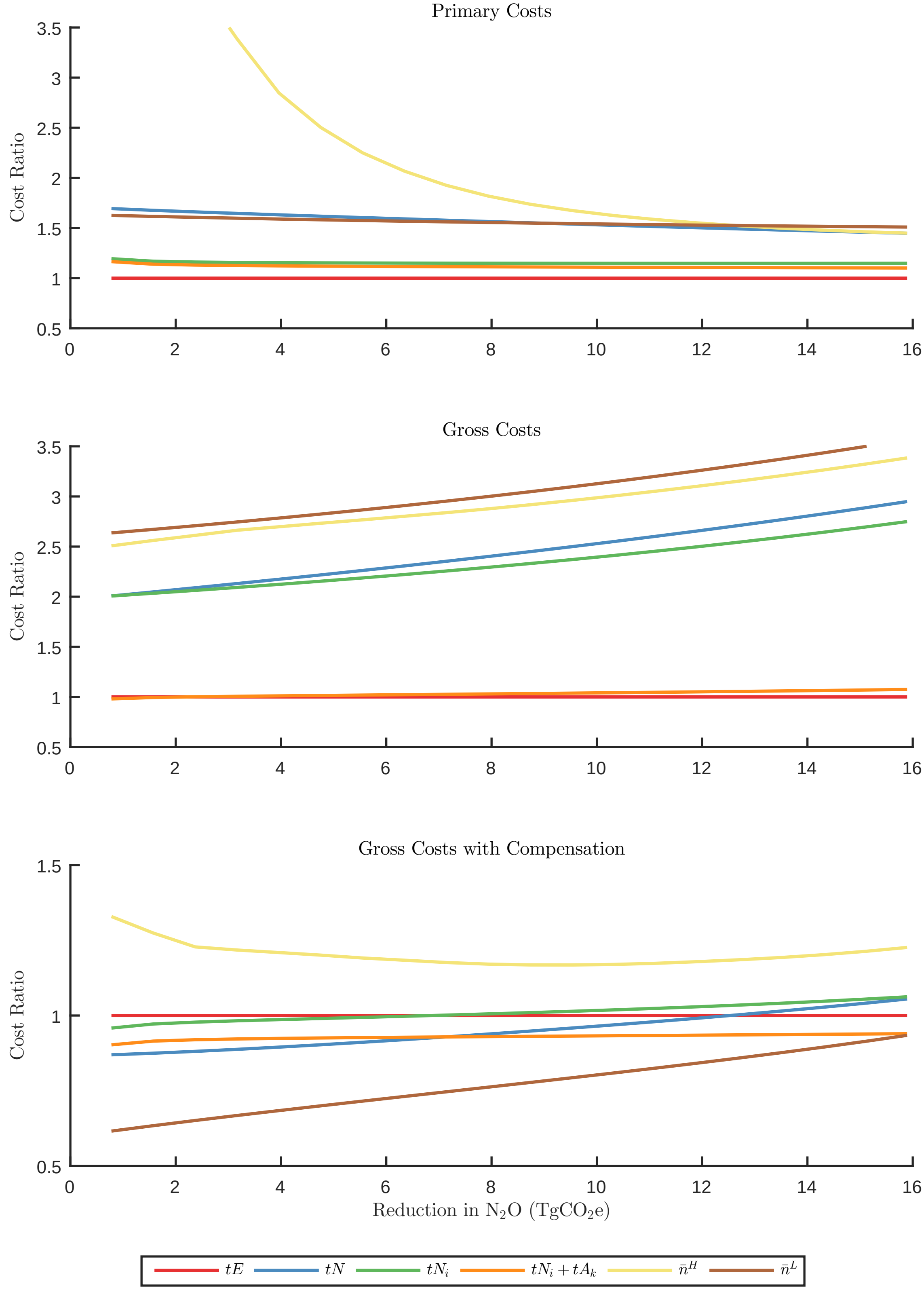


Figure 4: Costs of Alternative Policies



Notes: Cost ratios are relative to the emissions tax. When the costs of the emissions tax and the alternative policy have different signs, one plus the percent difference in costs, relative to the absolute value of costs of the emissions tax, is plotted instead.

Appendix

A.1 Deriving Analytical Results

A.1.1 Derivations of Marginal Primary Cost Formulas

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

$$V\left(P_1 \dots P_K, \Pi_A, G\right) = \max_{C_1,\dots,C_k,C} U(C_1,\dots,C_k,C) + \lambda_I \left[G_C + \Pi_A + \bar{L} - \sum_k P_k C_k - C\right] \tag{A.1}$$

and from the envelope theorem:

$$\frac{\partial V}{\partial P_k} = -\lambda_I C_k \qquad \frac{\partial V}{\partial \Pi_A} = \frac{\partial V}{\partial G_C} = \lambda_I. \tag{A.2}$$

Totally differentiating V with respect to a generic policy Φ yields:[1]

$$\begin{aligned}
\frac{dV}{d\Phi} &= \sum_k \frac{\partial V}{\partial P_k}\frac{dP_k}{d\Phi} + \frac{\partial V}{\partial \Pi_A}\frac{d\Pi_A}{d\Phi} + \frac{\partial V}{\partial G_C}\frac{dG_C}{d\Phi} \\
&= -\lambda_I \sum_k C_k \frac{dP_k}{d\Phi} + \lambda_I\left(\frac{d\Pi_A}{d\Phi} + \frac{dG_C}{d\Phi}\right) \\
-\frac{1}{\lambda_I}\frac{dV}{d\Phi} &= \sum_k C_k \frac{dP_k}{d\Phi} - \frac{d\Pi_A}{d\Phi} - \frac{dG_C}{d\Phi}
\end{aligned} \tag{A.3}$$

where the second line substitutes in the values from equation (A.2).

Likewise, the indirect profit function is:

$$\Pi_A\left(P_1 \dots P_K, \Phi\right) = \sum_{ij}\left(\max_{\boldsymbol{A}_{ij},\boldsymbol{n}_{ij}} \sum_k \pi_{ijk} A_{ijk} - L_{ij} + \lambda_{ij}\left[\bar{A}_{ij} - \sum_k A_{ijk}\right]\right) \tag{A.4}$$

and

$$\frac{\partial \Pi_A}{\partial \Phi} = \sum_{ijk} A_{ijk}\frac{\partial \pi_{ijk}}{\partial \Phi} \qquad \frac{\partial \Pi_A}{\partial P_k} = \sum_{ij} A_{ijk} y_{ijk} = Y_k. \tag{A.5}$$

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

$$\frac{d\Pi_A}{d\Phi} = \sum_k \frac{\partial \Pi_A}{\partial P_k}\frac{dP_k}{d\Phi} + \frac{\partial \Pi_A}{\partial \Phi} = \sum_k Y_k \frac{dP_k}{d\Phi} + \sum_{ijk} A_{ijk}\frac{\partial \pi_{ijk}}{\partial \Phi}. \tag{A.6}$$

Recognizing that $Y_k = C_k$ in equilibrium, and plugging equation (A.6) into equation (A.3) yields:

$$-\frac{1}{\lambda_I}\frac{dV}{d\Phi} = -\sum_{ijk} A_{ijk}\frac{\partial \pi_{ijk}}{\partial \Phi} - \frac{dG_C}{d\Phi} \tag{A.7}$$

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

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

Emissions Tax For an emissions tax, $\frac{dG_C}{dt_E} = t_E \frac{dE}{dt_E} + E$ and $\frac{\partial \pi_{ijk}}{\partial t_E} = e_{ijk}$. Plugging these expressions into equation (A.7) 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:

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

along with the relationship $t_E = \frac{P_k y^n_{ijk} - 1}{e^n_{ijk}}$ which is the first order conditions for input use.

Uniform Input Tax For a uniform input tax, $\frac{dG_C}{dt_N} = t_N \frac{dN}{dt_N} + N$ and $\frac{\partial \pi_{ijk}}{\partial t_N} = n_{ijk}$, so (A.7) 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:

$$\frac{dN}{dtN} = \sum_{ijk} n_{ijk} \frac{dA_{ijk}}{dtN} + \sum_{ijk} A_{ijk} \frac{dn_{ijk}}{dtN} \tag{A.8}$$

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

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

Input Rate Restriction Since the government does not collect revenue $G_C = 0$. For any parcel/crop combination where the input rate restriction is binding $n_{ijk} = \bar{n}_k$ and for these parcels $\frac{\partial \pi_{ijk}}{\partial \bar{n}_k} = P_k y^n_{ijk} - 1$. Substituting into equation (A.7) yields equation (11).

A.1.2 Derivation of Marginal Gross Cost Formula

In this section I derive the marginal gross costs for an emissions tax. As mentioned in the main text, an analogous procedure could be used to derive the marginal gross costs for the other instruments. Given that the government payment and agricultural profit, after compensation, are fixed, the indirect utility function is:

$$V\left(P_1 \dots P_K, tL\right) = \max_{C_1,\dots,C_k,C} U(C_1,\dots,C_k,C,\bar{L}-L) + \lambda_I \left[G_C + \Pi^0_A + (1-tL)L - \sum_k P_k C_k - C\right]. \tag{A.9}$$

Total differentiating the indirect utility function and plugging in $\frac{\partial V}{\partial P_k} = -\lambda_I C_k$ and $\frac{\partial V}{\partial tL} = -\lambda_I$ from the envelope theorem and rearranging yields:

$$-\frac{1}{\lambda_I}\frac{dV}{dtE} = \sum_k C_k \frac{dP_k}{dtE} + L\frac{dtL}{dtE} \tag{A.10}$$

The government's budget constraint is:

$$G_C + \left(\Pi_A^0 - \Pi_A\right) = tEE + tLL. \tag{A.11}$$

Fixing G_C and totally differentiating yields:

$$\frac{dtL}{dtE} = \frac{-\left(E + tE\frac{dE}{dtE} + tL\frac{dL}{dtE} + \frac{d\Pi_A}{dtE}\right)}{L + tL\frac{\partial L}{\partial tL}} \tag{A.12}$$

Substituting this equation and the definition of M into equation (A.10) and canceling terms yields 12.

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 A.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).[2] 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.

[2] 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).

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.[3] These shares are used to construct the baseline production and consumption data presented in Table A.1.

Sector Definitions The definitions of intermediate sectors are as follows. 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.

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 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.[4] 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.[5] 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

[3]The detailed producer price NIPA IO tables after redefinition are used.
[4]Imports of processed soybeans (mean and oil) are also very small less than 1% of US consumption.
[5]A larger share of corn for ethanol is used because in more recent years ethanol production becomes more prominent in later years.

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.[6]

Soybeans are either exported or processed into meal and oil.[7] Soybean meal and oil are then used as food or feed and can be exported.[8] 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, 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.[9] 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.

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

[7]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.

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

[9]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.

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.[10] 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 overhead.[11] 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.9. 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.

[10] 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.

[11] 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.

A.3 Biophysical Model

Yield Function Calibration

Generating the marginal yield information used for calibration requires four key steps.[12] First, the derivatives of the yield response functions are evaluated at the baseline region average N application rates n_0 and a 5% reduction from the baseline rate, n_1. Denote the marginal yields at these rates as dy_0 and dy_1 respectively. Second, dy_0 and dy_1 are replaced with the region-crop averages for any crop-parcel with positive marginal yields. Likewise, dy_1 is replaced according to the region-crop average change in dy for all crop-parcel pairs for which $dy_1 <= dy_1$. Third, dy_0 are adjusted to fall within 10% of the state-crop median marginal yields. This adjustment prevents extreme differences in predicted N application rates across parcels in each state. For any dy_0 values that were adjusted, dy_1 is rescaled to preserve the percent difference between dy_0 and dy_1. Fourth, marginal yields are scaled to achieve the desired yield elasticity with respect to N applications.

Using the cleaned marginal yield values, the parameters of the variable portion of the yield function are calibrated according to:

$$\beta = 1 + \frac{\ln\left(\frac{dy_1}{dy_0}\right)}{\ln\left(\frac{n_1}{n_0}\right)}$$
$$\gamma = \frac{dy_0}{\beta n_0^{\beta-1}}. \tag{A.13}$$

The first equation sets β to reflect the change in marginal yields due to reduced N applications, while the second equation ensures that marginal yields match dy_0 at the baseline N application rate. The final step in calibration is to set $\hat{y}$ such that predicted yields match observed yields at the N application rates predicted under baseline prices.

[12] Although the subscripts are dropped in what follows, this procedure is conducted for all crop-parcel combinations.

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

A. US

	Endow, Supply	HAY	SB	ETOH	MEAT	F	C	CF	U
L	15,107.6		9.29	5.97	84.45	216.17	9,300.73		5,416.67
Corn	64.03			16.14	29.45	6.92			
W. Wheat	9					4.41			
Sorghum	2.98				1.39				
Cotton	5.03						1.26		
Grass Hay	6.69	6.69							
Alfalfa	7.94	7.94							
Soybean	32.9		19.74						
O	4.81						4.81		
HAY					14.63				
SB					18.87	4.35			
ETOH							22.1		
MEAT					52.28	148.8			
F						89.29		380.64	
C								9,369.36	
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			11.53					11.53
W. Wheat			4.59					4.59
Sorghum			1.59					1.59
Cotton			3.77					3.77
Soybean			13.16					13.16
SB			5.81					5.81
AG, ROW				1,170				
AG, US				40.45				
AG					1,210.45			
F							2,241.58	
C							27,008.42	-40.45

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 $59.06 billion.

Table A.2: 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.

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 Application Rates (kg/ha)

Region	Corn	W. Wheat	Sorghum	Cotton	Grass Hay	Alfalfa	Soybean
Corn Belt	162.79	59.06		103.23	162.00	0.00	2.64
Plains	149.92	69.03	82.26		173.45	0.00	7.12
Lake States	131.18	58.82			173.41	0.00	4.05
Northeast	88.49	59.04			122.03	0.00	4.36
Pacific Northwest	185.34	59.53			173.18	0.00	
California	185.73	75.34		143.78	173.40	0.00	
Mountains	141.11	57.92	34.44		165.23	0.00	4.57
South Central	185.47	59.47	63.13	112.11	180.86	0.00	6.54
Southeast	151.99	59.45		93.97	155.21	0.00	8.40
Southwest	150.27	60.76	66.05	63.56	147.76	0.00	4.40
National	153.42	63.12	72.67	85.87	163.36	0.00	4.53

Notes: Average predicted mineral N application rates at baseline prices.

Table A.5: Baseline N Applications (million tonnes)

Region	Corn	W. Wheat	Sorghum	Cotton	Grass Hay	Alfalfa	Soybean
Corn Belt	2.61	0.06		0.02	0.28		0.03
Plains	1.25	0.34	0.09		0.39		0.04
Lake States	0.73	0.02			0.07		0.02
Northeast	0.07	0.01			0.09		0.00
Pacific Northwest	0.01	0.06			0.05		
California	0.01	0.01		0.01	0.03		
Mountains	0.07	0.12	0.00		0.15		0.00
South Central	0.34	0.05	0.01	0.10	0.44		0.02
Southeast	0.11	0.03		0.07	0.10		0.01
Southwest	0.12	0.16	0.06	0.10	0.36		0.00
Total	5.33	0.83	0.16	0.30	1.95	0.00	0.13

Table A.6: Baseline N_2O Emission Rates (tCO_2e/ha)

Region	Corn	W. Wheat	Sorghum	Cotton	Grass Hay	Alfalfa	Soybean
Corn Belt	2.72	1.14		1.78	2.46	1.10	1.60
Plains	1.33	0.55	0.71		1.51	1.07	0.94
Lake States	2.15	1.07			2.29	1.02	1.57
Northeast	1.62	1.02			1.83	1.19	1.47
Pacific Northwest	1.69	0.40			1.46	1.29	
California	1.79	1.24		1.71	1.72	1.32	
Mountains	1.43	0.71	0.62		1.78	0.96	1.08
South Central	2.12	0.92	1.05	1.50	2.22	0.84	1.06
Southeast	1.59	0.86		1.23	1.69	0.96	1.06
Southwest	1.61	0.74	0.77	1.03	1.81	2.10	1.35
National	2.16	0.70	0.76	1.24	1.93	1.08	1.36

Notes: Average emissions rates calculated using predicted N application rate at baseline prices.

Table A.7: Baseline N_2O ($TgCO_2e$)

Region	Corn	W. Wheat	Sorghum	Cotton	Grass Hay	Alfalfa	Soybean
Corn Belt	43.61	1.10		0.26	4.19	0.76	20.76
Plains	11.12	2.72	0.75		3.36	2.03	5.94
Lake States	11.90	0.28			0.97	1.10	6.40
Northeast	1.28	0.15			1.33	0.39	0.67
Pacific Northwest	0.11	0.38			0.42	0.40	
California	0.13	0.13		0.11	0.31	0.47	
Mountains	0.73	1.44	0.04		1.63	1.64	0.00
South Central	3.87	0.70	0.19	1.38	5.36	0.07	3.43
Southeast	1.14	0.37		0.94	1.06	0.02	1.06
Southwest	1.30	1.95	0.72	1.69	4.37	0.27	0.15
Total	75.20	9.22	1.70	4.39	23.02	7.15	38.40

Table A.8: Marginal Abatement Costs of Changing Inputs

Region	Corn	W. Wheat	Sorghum	Cotton	Grass Hay	Alfalfa	Soybean
Corn Belt	2.90	43.47		5.08	4.81	N/A	N/A
Plains	12.35	296.90	23.72		13.37	N/A	N/A
Lake States	3.93	86.17			8.07	N/A	N/A
Northeast	25.07	45.28			10.70	N/A	N/A
Pacific Northwest	3.03	294.26			15.72	N/A	
California	7.32	162.02		3.70	24.36	N/A	
Mountains	19.86	274.18	150.04		3.89	N/A	N/A
South Central	3.50	86.40	2.60	7.73	2.64	N/A	N/A
Southeast	2.62	73.87		17.14	6.29	N/A	N/A
Southwest	5.53	143.37	93.30	91.64	71.55	N/A	N/A
National	6.19	216.65	54.57	48.56	20.55	N/A	N/A

Notes: Partial equilibrium marginal abatement costs ($) for changing N application rates at 0.05 tCO_2e/ha reduction. A maximum cost of 300 \$/tCO_2e is imposed for each crop and county. No abatement through N application rate changes is available for legume crops.

Table A.9: 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

Table A.10: Policy Costs Under Alternative Parameter Assumptions (10% Reduction)

	tE million \$	tN	tN_i	$tN_i + tA_k$	$\bar{n}^H$	$\bar{n}^L$
		Ratio to tE				
Primary Costs						
Central	517.81	1.45	1.15	1.10	1.45	1.51
Low η_A	537.80	1.43	1.13	1.10	1.39	1.44
High η_A	503.28	1.47	1.17	1.10	1.50	1.57
Low η_Y	370.72	1.40	1.12	1.09	1.43	1.46
High η_Y	678.82	1.50	1.17	1.11	1.46	1.56
Low η_F	528.32	1.46	1.15	1.10	1.46	1.52
High η_F	508.32	1.44	1.15	1.10	1.44	1.50
Low η_L	517.95	1.45	1.15	1.10	1.45	1.51
High η_L	517.67	1.45	1.15	1.10	1.45	1.51
Gross Costs						
Central	-878.12	2.95	2.75	1.07	3.38	3.56
Low η_A	-909.29	2.95	2.75	1.07	3.35	3.53
High η_A	-857.37	2.95	2.75	1.08	3.41	3.59
Low η_Y	-578.47	3.08	2.88	1.09	3.55	3.74
High η_Y	-1224.42	2.86	2.66	1.06	3.27	3.46
Low η_F	-884.66	2.98	2.78	1.08	3.42	3.61
High η_F	-872.17	2.92	2.72	1.07	3.35	3.52
Low η_L	-575.08	3.42	3.12	1.11	3.94	4.17
High η_L	-1194.58	2.71	2.56	1.06	3.11	3.26
Gross Costs with Compensation						
Central	-904.80	1.05	1.06	0.94	1.23	0.93
Low η_A	-926.87	1.00	1.01	0.94	1.16	0.86
High η_A	-881.73	1.10	1.11	0.94	1.28	1.00
Low η_Y	-765.21	1.03	1.05	0.94	1.20	0.92
High η_Y	-1016.82	1.08	1.07	0.94	1.26	0.96
Low η_F	-962.97	1.05	1.06	0.94	1.21	0.93
High η_F	-852.72	1.06	1.06	0.94	1.24	0.94
Low η_L	-595.24	1.15	1.10	0.95	1.35	1.02
High η_L	-1228.50	1.01	1.04	0.94	1.16	0.89

Table A.11: Policy Impacts Under Alternative Parameter Assumptions (10% Reduction)

	tE	tN	tN_i	$tN_i + tA_k$	$\bar{n}^H$	$\bar{n}^L$
ΔP_F						
	%	Ratio to tE				
Central	1.76	1.13	1.02	1.07	1.08	1.22
Low η_A	1.83	1.15	1.05	1.07	1.11	1.24
High η_A	1.70	1.11	1.00	1.07	1.06	1.20
Low η_Y	1.40	1.11	1.01	1.06	1.07	1.20
High η_Y	2.10	1.15	1.04	1.08	1.10	1.24
Low η_F	1.84	1.13	1.02	1.07	1.09	1.22
High η_F	1.68	1.13	1.02	1.07	1.08	1.22
Low η_L	1.76	1.13	1.02	1.07	1.08	1.22
High η_L	1.76	1.13	1.02	1.07	1.08	1.22
Δ Env. Taxes						
	$/ha	Ratio to tE				
Central	107.12	0.26	0.24	1.00	0.00	0.00
Low η_A	111.63	0.26	0.24	1.01	0.00	0.00
High η_A	103.88	0.26	0.24	1.00	0.00	0.00
Low η_Y	76.33	0.25	0.24	1.00	0.00	0.00
High η_Y	140.94	0.27	0.25	1.01	0.00	0.00
Low η_F	109.46	0.26	0.24	1.00	0.00	0.00
High η_F	105.03	0.26	0.24	1.00	0.00	0.00
Low η_L	107.15	0.26	0.24	1.00	0.00	0.00
High η_L	107.10	0.26	0.24	1.00	0.00	0.00
Δ Ag. Profit						
	$/ha	Ratio to tE				
Central	1.11	86.05	76.85	7.12	97.74	119.37
Low η_A	0.57	177.83	159.21	13.26	200.15	243.92
High η_A	0.99	90.95	80.96	7.66	104.27	127.53
Low η_Y	10.22	7.55	6.81	1.54	8.33	10.12
High η_Y	-12.20	-9.18	-8.10	0.37	-10.71	-13.17
Low η_F	4.00	25.20	22.47	2.81	28.47	34.73
High η_F	-1.48	-61.00	-54.56	-3.32	-69.64	-85.20
Low η_L	1.14	83.64	74.69	6.96	94.98	116.00
High η_L	1.07	88.62	79.14	7.29	100.66	122.94

Figure A.1: Included Counties