This dissertation is composed of three essays. The purpose of the first essay is to investigate the effect that higher temperatures have on the size of wildfires in the western United States controlling for suppression effort, precipitation, and other factors. Using data for 466 wildfires that occurred on U.S. Forest Service land between 2003 and 2007, I find that an increase in temperature of 1°C is associated with a 12% increase in wildfire size, holding all other factors constant. Given that current climate models predict temperatures to rise by 1.6 to 6.3°C, this estimate suggests mean wildfire size could increase by 20% to 79%. Off-setting this increase in wildfire size would require an increase in suppression expenditures of at least 16% to 63%. For the average wildfire, this would translate into an increase in suppression expenditures of between $0.5 and $2 million.

The purpose of the second essay is to investigate whether weed mobility has created a tragedy of the commons problem for soybean growers that hastened the emergence of glyphosate-resistant weeds. To determine whether this was the case, I derive a set of testable predictions from a simple game theoretic model of herbicide applications. Specifically, the model predicts that weed mobility will lead glyphosate application rates to increase as the number of neighbors surrounding a grower increases. I test this hypothesis using data for over 2,000 soybean growers collected during the 2006 Agricultural Resource Management Survey. I do not find evidence that the emergence of glyphosate resistance was the result of a national “tragedy of the commons” problem. Instead, my results suggest that strategic
externalities only dominated other external factors in areas that are densely populated by soybean growers.

The purpose of the third essay is to investigate how growers respond to declines in herbicide susceptibility. I investigate this question using a panel of state-level glyphosate application data for cotton and soybean growers in the United States from 1996 to 2002. My results indicate that growers responded to declines in glyphosate susceptibility during this period by decreasing their use of glyphosate.
Three Essays in Agricultural and Natural Resource Economics

by
Dallas Wayne Wood

A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Economics

Raleigh, North Carolina

2015

APPROVED BY:

_______________________________  ________________________________
Walter N. Thurman  Jeffrey Prestemon
Committee Chair

_______________________________  ________________________________
Roger H. von Haefen  Michele Marra
DEDICATION

To my wife Andrea for her endless patience
BIOGRAPHY

The author was born in North Carolina in 1981. He earned his bachelor's degree in economics from North Carolina State University in 2005. He earned his master's degree in economics from North Carolina State University in 2012.
ACKNOWLEDGMENTS

My deepest gratitude goes to my advisor Walter N. Thurman. This dissertation would not have been completed without his deep insight and encouragement. I would like to thank my committee members Jeffrey Prestemon, Roger H. von Haefen and Michele Marra for their helpful comments and advice. I also greatly appreciate the feedback I received from a number of different scholars I met as a fellow at the Property and Environment Research Center. In particular, special thanks to Dan Benjamin (formerly) of Clemson University and Joe Atwood of Montana State University. I also deeply appreciate the help and friendship offered by my fellow graduate students in the department—Steve Dundas, Chris Giguere, Kelsey Hample, Parker Sheppard, Kole Swanser, and Steve Tsang. They taught me as much as my professors and made an otherwise stressful process a happy journey. I thank my parents, Bobby and Collette, for their constant encouragement. Not just in this, my latest endeavor, but in all my efforts that have contributed to my character. I thank my brother, Brian, for love and support. Finally, I thank my wife, Andrea, without further explanation because any attempt would fall woefully short of conveying her value to this effort.
## TABLE OF CONTENTS

List of Tables .................................................................................................................. vii

List of Figures ................................................................................................................ viii

Chapter 1 An Economic Approach to Measuring the Impacts of Higher Temperatures on Wildfire Size in the Western United States.............................................................01

1.1 Introduction..................................................................................................................01

1.2 Factors Influencing Wildfire Size..............................................................................03

1.3 An Economic Model of Wildfire Size........................................................................08

1.4 Estimating the Economic Model.................................................................................11

1.4.1 Included Variables...............................................................................................11

1.4.2 Functional Form..................................................................................................13

1.4.3 Estimator and Choice of Instrument.................................................................15

1.5 Data..........................................................................................................................19

1.5.1 Exogenous Variables...........................................................................................20

1.5.2 Endogenous and Instrumental Variables........................................................22

1.6 Results.......................................................................................................................22

1.7 Conclusion..................................................................................................................28

1.8 Figures and Tables....................................................................................................29

1.9 References................................................................................................................39
Chapter 2 Has Weed Mobility Created a Tragedy of the Commons that Hastened the Emergence of Glyphosate-Resistant Weeds? Evidence from U.S. Soybean Growers

2.1 Introduction..........................................................................................................................41

2.2 Background..........................................................................................................................44
  2.2.1 Weed Control Methods.................................................................................................45
  2.2.2 Herbicide Resistance.................................................................................................47

2.3 Weed Susceptibility as a Common Property Resource.................................................49

2.4 A Simple Game Theoretic Model of Herbicide Application...........................................53
  2.4.1 Define the Payoff Function..........................................................................................54
  2.4.2 Derive Best Response Function..................................................................................57
  2.4.3 Symmetric Nash Equilibrium.....................................................................................58
  2.4.4 Testable Predictions.....................................................................................................60

2.5 Estimating Partial Effect of Neighbor Density Glyphosate Application Rates............61
  2.5.1 Included Variables.........................................................................................................62
  2.5.2 Functional Form............................................................................................................64
  2.5.3 Estimator and Hypothesis Test.....................................................................................65

2.6 Data.......................................................................................................................................66

2.7 Results.....................................................................................................................................68

2.8 Conclusions..........................................................................................................................70

2.9 Figures and Tables...............................................................................................................72

2.10 References..........................................................................................................................83
Chapter 3 How Do Growers Respond to Declines in Herbicide Susceptibility? Evidence from U.S. Cotton and Soybean Growers

3.1 Introduction
3.2 Economic Models of Weed Management Behavior
   3.2.1 Exogenous Herbicide Susceptibility
   3.2.2 Endogenous Herbicide Susceptibility
   3.2.3 Summary of Predictions for Weed Management Behavior
3.3 Empirical Strategy
3.4 Data
3.5 Results
   3.5.1 Cotton Growers
   3.5.2 Soybean Growers
3.6 Conclusions
3.7 Figures and Tables

Appendices
   A.1 Exogenous Herbicide Susceptibility
   A.2 Figures and Tables
LIST OF TABLES

Table 1.1. Descriptive Statistics.................................................................33
Table 1.2. Results from First-Stage of TSLS Regression for Model 1...............34
Table 1.3. Results from First-Stage of TSLS Regression for Model 2..............35
Table 1.4. TSLS Estimation Results for Wildfire Size Model 1.........................36
Table 1.5. TSLS Estimation Results for Wildfire Size Model 1........................37
Table 1.6. OLS Estimation Results for Wildfire Size Models 1 and 2...............38
Table 2.1. Descriptive Statistics of Soybean Grower Characteristics (n=2,258).....79
Table 2.2. OLS Estimates for Model 1..........................................................80
Table 2.3. Testing Partial Effect of Neighbor Density on Glyphosate Application Rate..81
Table 2.2. OLS Estimates for Model 2..........................................................82
Table 3.1. Summary Statistics........................................................................116
Table 3.2 First-Stage Results from Model 1 Estimation....................................117
Table 3.3. First-Stage Results from Model 2 Estimation....................................118
Table 3.4. Model 1 Estimates for Cotton Growers..........................................119
Table 3.5. Model 2 Estimates for Cotton Growers..........................................120
Table 3.6. Model 1 Estimates for Soybean Growers........................................121
Table 3.7. Model 2 Estimates for Soybean Growers........................................122
LIST OF FIGURES

Figure 1.1. Illustration of Economic Model ................................................................. 29
Figure 1.2. Total Timber Cut on USFS land by Region 1980-2013 ................................. 30
Figure 1.3. Location of Wildfires Included in Dataset .................................................. 31
Figure 1.4. Linear Relationships between Mean Temperature and log Wildfire Size ....... 32
Figure 2.1. Confirmed glyphosate-resistant weed populations in North America ........... 72
Figure 2.2. Herbicide Use Practices on Soybean Acres (1996-2012) ......................... 73
Figure 2.3. Diversity of Herbicide Use by Soybean Growers (1995-2005) .................... 74
Figure 2.4. Impact of Neighbors on Effectiveness of Resistance Management Practices ... 75
Figure 2.5. Nash Equilibrium Glyphosate Use ............................................................ 76
Figure 2.6. USDA Farm Production Regions ............................................................... 77
Figure 2.7. County Farm Density in U.S. and Appalachian Region ......................... 78
Figure 3.1. Confirmed glyphosate-resistant weed populations in North America ....... 110
Figure 3.2. Static Profit-Maximizing Level of Herbicide Application ............................ 111
Figure 3.3. Lifetime Profit-Maximizing Level of Herbicide Application ..................... 111
Figure 3.4. Profit-Maximizing Timepath with Conventional Production Function ........ 112
Figure 3.5. Cotton Grower Glyphosate Application Rates and Mean Glyphosate Prices .... 112
Figure 3.6 Soybean Grower Glyphosate Application Rates and Mean Glyphosate Prices 113
Figure 3.7. States included in Cotton Panel Dataset ...................................................... 113
Figure 3.8. States included in Soybean Panel Dataset .................................................. 114
Figure 3.9. Linear Relationship between glyphosate application rates in period t-1 (horizontal axis) and the difference between glyphosate application rates in t and t-1 (vertical axis) for U.S. Cotton growers.................................114

Figure 3.10. Linear Relationship between glyphosate application rates in period t-1 (horizontal axis) and the difference between glyphosate application rates in t and t-1 (vertical axis) for U.S. Soybean growers.................................115

Figure A.1 Profit-Maximizing Level of Herbicide Application..........................129

Figure A.2. Consequences of Decline in Susceptibility Stock.............................129
CHAPTER 1

An Economic Approach to Measuring the Impacts of Higher Temperatures on Wildfire Size in the Western United States

1.1. Introduction

Over the past thirty years, the average size of wildfires in the United States has more than doubled, from 15 hectares per fire in the 1980s to 36 hectares per fire in the 2000s (NIFC, 2014). Much of this increase was driven by a growing number of catastrophic wildfires that exceed 20,000 hectares like the 2002 Hayman Fire in Colorado that burned 55,846 hectares and destroyed $38.7 million in private property (USFS, 2013). Policy makers interested in responding to these events need to understand what is driving this trend.

Previous studies by ecologists and other natural scientists suggest that increases in wildfire activity have been largely driven by changes in weather variables—namely higher temperatures. The first of these studies was McKenzie et al. (2004), which regressed the number of wildfire acres burned in 11 western states from 1916-2002 on mean summer temperature and precipitation for each state. This study found that years with high summer temperatures were associated with more acres burned by wildfire.

Subsequent studies applied similar analytical methods to more spatially disaggregated datasets and found analogous results (Westerling et al., 2006; Littell et al., 2009). However, none of these studies controlled for human efforts to suppress wildfire in their regression estimates. This is important because one would expect suppression to both have a significant
influence on wildfire size and be correlated with temperature for a variety of reasons. For example, higher temperatures could be associated with less suppression effort if warmer weather made conditions more dangerous for fire fighters (e.g. higher risk of heat stroke). Alternatively, higher temperatures could be associated with more suppression effort if dryer fuels mean more economic resources are threatened by fire. In either case, by excluding suppression effort, these previous studies may have significantly over (or under) stated the impact of higher temperatures on wildfire activity due to omitted variable bias.

However, trying to overcome the omitted variable problem by adding a measure of suppression effort to a regression model can introduce new problems. Specifically, wildfire size and suppression effort are jointly determined, which means that an instrumental variable estimator must be used to avoid the problem of endogeneity bias. This issue was previously identified by Johnston and Klick (2011), but they did not attempt to estimate such a model themselves.

The goal of this paper is to fill this gap in the existing literature by estimating the partial effect of temperature on wildfire size while controlling for suppression effort using data from wildfires on U.S. Forest Service land. First, I develop an economic model where wildfire size is determined by the interaction of exogenous natural factors, such as mean temperature and precipitation when a fire is ignited and in previous months, and suppression effort applied by U.S. Forest Service fire managers. Specifically, I follow Donovan and Rideout (2003) and assume the objective of fire managers is to minimize the sum of costs associated with wildfire (i.e. the cost of suppression effort plus the cost of net wildfire
damages). Next, I estimate the structural equations derived from this model using data collected from a pooled cross section of 466 wildfires that occurred in the western United States between 2003 and 2007 and for which there is reliable suppression expenditure data (a proxy for suppression effort). Estimates for temperature and precipitation for the area surrounding each fire are estimated using weather-station level data obtained from the National Climate Data Center from its Global Historical Climatology Network (GHCN) Monthly database.

The remainder of the paper is organized as follows. First, I discuss the scientific literature on wildfire size to identify factors that can influence wildfire size. Second, I develop an economic model of wildfire that accounts for human suppression activity. Third, I describe the methods used to estimate the economic model I develop. Fourth, I report the results of this estimation. The paper concludes with a discussion of the results and limitations of the paper.

1.2. Factors Influencing Wildfire Size

The number of hectares a wildfire will burn after it has been ignited primarily depends on five factors: 1) the stock of available biomass to burn (i.e. fuel availability), 2) the combustibility of that biomass (i.e. fuel flammability), 3) the ecology of the surrounding area, 4) the topography of the surrounding area, and 5) how much effort is exerted to suppress the fire. In the following section, I will describe how each of these factors influence the size of wildfires.
The stock of fuel available for wildfires to burn consists of different types of biomass such as dead woody material (needles, fallen branches, dried herbaceous vegetation, snags, and logs), shrubs, live trees and other vegetation (Bracmort, 2013). Each of these types of fuel contributes to wildfire activity in different ways. For example, fuels that are small in diameter, such as needles and leaves, are most important for how quickly a wildfire will spread. This is because their small size means they lose moisture quickly and therefore combust more easily (Bracmort, 2013). By contrast, larger fuels, such as branches, shrubs, and logs, are more important for how intense the wildfire will become (i.e. how much energy a wildfire will release as it burns) (Bracmort, 2013).

How much fuel is accumulated over a particular period of time depends on how much fuel is grown over that period and how much is removed. Biomass growth is supported by environmental factors such as precipitation. Precipitation in the months immediately preceding a wildfire are most important for determining the quantity of small diameter fuels that are available to burn, while atmospheric conditions over longer periods of time are more important for larger fuels because they take longer to grow.

Biomass removal can be accomplished by two methods: 1) naturally by wildfire or 2) artificially by timber harvesting or fuel removal. However, from 1935 to 1971, biomass removal by wildfire was severely limited. This is because the U.S. government was committed to a policy of suppressing all wildfires (regardless of potential benefits). This policy was known as the “10AM policy” as it called for the “fast, energetic, and thorough suppression of all fires in all locations, during possibly dangerous fire weather. When
immediate control is not thus attained...the [suppression] each succeeding day will be
planned and executed with the aim, without reservation, of obtaining control before ten
o’clock the next morning” (Donovan et al., 2008). As a result of this complete suppression
policy, tons of biomass that would have historically been removed by wildfire accumulated,
contributing to the growing size of wildfires.

In 1979, the 10AM policy was abandoned for one where the amount and timing of
suppression effort was guided by benefit-cost analysis. However, over time, it became clear
that the consequences of following the 10AM policy for decades were not eliminated simply
by abandoning the policy itself. Ecologists argued that many areas suffered from excess fuel
loads created by the exclusion of wildfires in the past that made the likelihood of larger
wildfires in the future even greater. These concerns led the federal government to pursue
artificial fuel removal starting in the early in 2000s.

Once fuel has accumulated, its flammability is primarily determined by moisture
content. Specifically, fuel with a moisture content of up to 20%-30% can be ignited by a
match, spark from a chainsaw, or more commonly from lightning (Bracmort, 2013). Moisture
content is primarily determined by weather conditions prior to a fire’s ignition. Higher
temperatures will increase the drying capacity of the air and lower precipitation levels will
make less moisture available (Routlet et al., 1992; Flannigan et al., 2009). For fine fuels,
weather conditions in the weeks immediately preceding a fire are most important, because
they are small and their moisture content can therefore change quickly (Bracmort, 2013).
In addition to fire availability and flammability, the ecosystem surrounding a fire determines how fuel availability and flammability interact to influence wildfire size. For example, in a relatively dry ecosystem that is dominated by grass and low density shrub vegetation types, fuel coverage may be so sparse that in some years the spread of large fires is limited by fuel availability. When such an ecosystem receives above normal precipitation, fire risks may be subsequently elevated for a time, as excess moisture leads to the growth of additional vegetation that can provides more continuous fuel coverage (Westerling and Bryant, 2008). Westerling and Bryant (2008) refer to these systems as moisture-limited fire regimes.

The topography of the area surrounding the fire is also important for how large it will grow. The three topographical characteristics that are most relevant for fire size are aspect, elevation, and slope. Aspect is the direction of the slope and it affects how much solar radiation a site receives. South facing slopes receive much higher solar radiation, so fuels tend to dry out sooner and more thoroughly during the fire season. Elevation affects fire behavior by influencing the amount and timing of precipitation, as well as exposure to prevailing wind. Slope influences the speed of a wildfire’s spread. Specifically, as heat rises in front of the fire, it more effectively preheats and dries upslope fuels, making for more rapid combustion.

In addition to the geophysical aspects discussed above, human beings also have significant influence over how large a wildfire will grow through the amount of effort they exert on suppressing the fire. In the United States, there are multiple local, state, tribal, and
Federal organizations tasked with fighting wildfires, with each organization being responsible for responding first to wildfires occurring within their jurisdiction (very large fires may require coordination of resources across multiple organizations). If a fire occurs on a national forest or national grassland, it is the responsibility of the USFS to provide an initial response. These USFS lands are grouped into nine broad geographic areas known as USFS management regions (Figure 1). Each region is managed by a “regional forester.” However, the person that is actually in charge of controlling a particular fire is the incident commander.

The incident commander establishes priorities for the incident, develops strategies to accomplish these objectives, and must establish an organization and command structure for dealing with the blaze. If the incident commander behaves in accordance with the current USFS fire management policy described above, then his ultimate objective will be to minimize the sum of all monetized wildfire-related costs and damages. The specific costs of wildfire suppression will depend on the tactic used to suppress the wildfire. There are two primary fire suppression tactics incident commanders can pursue to suppress a fire: direct attack and indirect attack. A direct attack is conducted at a fire’s edge and involves applying treatments directly to burning fuel such as wetting, smothering, or chemically quenching the fire. An indirect attack is conducted a distance from the fire and typically involves actions like creating a gap between the fire and unburned fuel in order to break or slow the progress of wildfire. In either case, the costs of suppression can include the labor cost of paying fire crews and the material and capital costs of using and maintaining equipment like helicopters, planes, and bulldozers (Holmes and Calkin, 2012). The damages of wildfire include value of
lost timber and in some cases property damages (Donovan et al., 2008). In the next section, I formalize this general discussion about wildfire size into an economic model that can be estimated.

1.3. An Economic Model of Wildfire Size

Based on the discussion in the previous section, we can say that changes in temperature and precipitation in the weeks prior to a fire’s ignition influence its size through their effect on fuel flammability, while changes in these variables over a longer time period influence fire size through fuel availability. In addition to temperature and precipitation, fire size is also influenced by the level of effort exerted in suppressing the wildfire as well as the ecology and topography of the surrounding area. A general function determining wildfire size can be expressed as

\[
\text{Size}_i = f(T_i, P_i, \text{Fuel}_i, \text{Supp}_i, \text{Ecology}_i, \text{Aspect}_i, \text{Elev}_i, \text{Slope}_i)
\] (1)

where \text{Size}_i is the number of hectares burned by wildfire i, T is the average temperature for the area surrounding wildfire i in the month the fire occurred, P is the total precipitation for the area surrounding wildfire i in the month the fire occurred, \text{Fuel}_i is the fuel stock of the area surrounding wildfire i, \text{Supp}_i is the level of suppression effort applied in controlling wildfire i, \text{Ecology}_i is a dummy variable indicating which ecological region the fire occurred in, \text{Aspect}_i is the aspect at the point of ignition, \text{Elev}_i is the elevation the point of ignition, and \text{Slope}_i is the slope at the point of ignition.
Note that all of the factors included in this function are exogenous except for suppression effort. Suppression effort is necessarily jointly determined with the number of wildfire hectares burned. Therefore, if we wish to model how many hectares will be burned each period, we must also model the decision for how much suppression effort is applied each period.

To the extent the USFS is guided by benefit-cost analysis, it will seek to choose the level of suppression that minimizes the total cost (TC) of wildfire. Here, TC is defined as fire-suppression costs plus net fire damages, where net fire damages can include destruction of private property, destruction of harvestable timber, etc. (Husari and McKelvey, 1997; Donovan and Rideout, 2003). Under this assumption, the incident commander solves the following cost minimization problem:

\[
\min_{\{\text{Supp}_i\}} \quad TC(\text{Supp}_i) = W^s \text{Supp}_i + ND(\text{Size}_i(\text{Supp}_i), X_i^{ND})
\]  

(2)

where \(W^s\) is the price of suppression effort, \(\text{Supp}_i\) is the level of suppression effort, and ND is the level of net damages from wildfire. I assume that ND is a function of \(\text{Size}_i\) (which is itself a function of suppression effort) as well as numerous other exogenous factors, \(X_i^{ND}\), that may influence the value of damages associated with a fire of a given size (e.g. the value of property in a wildfire’s path).

The first and second order conditions for this cost minimization problem are:

---

1 If one were thinking about how to minimize the total cost of fire over time, then the costs associated with fuel removal and other “pre-suppression” activities would also be included. However, after a fire has ignited, pre-suppression is fixed and is irrelevant to the choice of suppression effort. Therefore, it is excluded from this model.
FOC: \[ W^S + \frac{\partial ND}{\partial Size_i} \frac{\partial Size_i}{\partial Supp_l} = 0 \] (3)

SOC: \[ \frac{\partial^2 ND}{\partial Size_i^2} \left( \frac{\partial Size_i}{\partial Supp_l} \right)^2 + \frac{\partial ND}{\partial Size_i} \frac{\partial^2 Size_i}{\partial Supp_l^2} > 0 \] (4)

The first order condition implicitly defines the optimal level of suppression effort that will be applied to controlling wildfire in accordance with USFS policy goals. Intuitively, this condition says that suppression effort will be applied until the marginal cost of that effort \((W^s)\) equals its marginal benefit in terms of avoided damages \((-\frac{\partial ND}{\partial Supp_l} = -\frac{\partial ND}{\partial Size_i} \frac{\partial Size_i}{\partial Supp_l})\).

The second order condition tells us marginal benefit must be decreasing with additional suppression effort \((-\frac{\partial^2 ND}{\partial Supp_l^2} = -\frac{\partial^2 ND}{\partial Size_i^2} \left( \frac{\partial Size_i}{\partial Supp_l} \right)^2 - \frac{\partial ND}{\partial Size_i} \frac{\partial^2 Size_i}{\partial Supp_l^2} < 0\). Figure 1.1 illustrates the cost minimizing choice of suppression effort.

Assuming that the conditions of the Implicit Function Theorem are satisfied, we can solve the first order condition for the optimal level of suppression effort, which will be a function of exogenous variables:

\[ Supp_l^*(W^S, X^{ND}_t, T_i, P_i, Fuel_i, Ecology_i, Aspect_i, Elev_i, Slope_i) \] (5)

Substituting this level of suppression back into Eq.1 yields the optimal wildfire size, which is the wildfire size we would observe in the data.

\[ Size_i^* = (T_i, P_i, Fuel_i, Supp_l^*, Ecology_i, Aspect_i, Elev_i, Slope_i) \] (6)

1.4. Estimating the Economic Model

In order to estimate the theoretical model derived above, one must choose which variables to include in the estimated model, the parametric functional form that will be used,
and select an estimator to estimate the parameters themselves. Each of these items is discussed below.

1.4.1 Included Variables

In terms of which variables to include in the estimated model, this question is largely answered by the economic model itself. However, some of the variables included in the economic model could not be included in this study model due to data limitations, so I had to use suitable proxies. First, actual suppression effort cannot be observed, so I use inflation-adjusted suppression expenditures. Expenditures make a reasonable proxy for suppression effort, since I would expect that more money being spent suppressing a fire would indicate more resources being applied to fight the fire. However, it is important to note that expenditures make an imperfect proxy as differences in expenditure may also reflect differences in the prices of suppression resources as well as differences in effort exerted.

Second, an explicit measure of the fuel stock present at each fire is not available, so I use a measure of average precipitation anomaly for the area surrounding the fire’s point of ignition. Precipitation anomaly estimates should make a reasonable proxy for fuel stock surrounding a particular fire, because (as previously discussed) higher than normal precipitation levels will support fuel growth and therefore be associated with greater fuel stocks (especially fine fuels). Calculating this variable is completed in two steps. First, precipitation anomaly for each month prior to the fire’s ignition is calculated as the difference between precipitation that was actually observed in that month and the mean.
precipitation for that month from 1980 to 2000. Second, a simple average is taken for the estimated precipitation anomaly across each of the six months prior to the fire’s ignition.

Third, the ecological characteristics of the area surrounding each fire are also difficult to determine. For the purposes of this study, I categorize fires based on whether or not they occurred in a “dry” ecosystem. A “dry” ecosystem is a region where annual losses of water through evaporation at the earth's surface exceed annual water gains from precipitation. As a result of this water deficiency, no permanent streams originate in “dry” ecosystems. To capture ecological differences closer to the fire itself, I also include a categorical variable for the type of vegetation observed at the fire’s point of ignition.

In addition to these proxies, I also included categorical variables for the USFS management region the fire was located in and the year in which the fire occurred to capture unobserved factors that differ across geographic regions and unobserved factors that are common to all regions but vary across time. Figure 1.2 provides an indication for how big USFS management regions are. For example, USFS region 6 includes Oregon and Washington.

1.4.2 Functional Form
A log-level functional form is used for this model specification because inspection of
the model residuals suggested that the underlying disturbances better approximated a normal
distribution. Therefore, in this analysis, I estimate the following model:

\[
\text{Model } \#1: \ln(\text{Size}_i) = \beta_0 + \beta_1 T_i + \beta_2 P_i + \beta_3 P_{\text{Anom},i} + \beta_4 \ln(\text{SuppExp}_i) + \beta_5 \text{Dry}_i \\
+ \beta_6 \text{Grass}_i + \beta_7 \text{Slope}_i + \beta_8 \text{Aspect}_i + \beta_9 \text{Elev}_i + \sum_j \beta_j \text{USFS}_j + \sum_k \beta_k \text{Year}_k + u_i \quad (7)
\]

The variables are defined as follows:

- \(\ln(\text{Size}_i)\) = the natural log of the number of hectares as burned by fire \(i\),
- \(T\) = average temperature (measured in °C) of the area surrounding fire \(i\) in the
  in the month it was ignited,
- \(P\) = total precipitation (measured in millimeters) in the area surrounding fire \(i\)
  in the month it was ignited,
- \(\ln(\text{SuppExp}_i)\) = natural log of federal suppression expenditures incurred
  fighting fire \(i\),
- \(P_{\text{Anom}}\) = average monthly precipitation anomaly for area surrounding fire \(i\)
  for the six months prior to its ignition.
- \(\text{Dry}\) = a dummy variable equaling 1 when fire \(i\) occurred in a dry ecoregion,
- \(\text{Grass}\) = a dummy variables equaling 1 when vegetation at the fire’s point of
  ignition was recorded as “grass,”
- \(\text{Aspect}\) = cosine of the recorded aspect at the point of ignition equaling 1 if the
  aspect is generally northward, -1 if the aspect is southward, and close to 0 if
  the aspect is either east or west,
- Elev = recorded elevation of the point of ignition in feet,
- Slope = recorded percentage slope at the point of ignition,
- USFS = dummy variable equaling 1 when fire i occurred in USFS region j,
- Year = is a dummy variable equaling 1 when fire i occurred in Year k,
- \( u \) = a random disturbance term.

In addition to estimating this main effects model, I also estimate a model where the variable for precipitation anomaly is interacted with the “dry” categorical variable. I estimate this model to see whether the partial effect of precipitation is different for moisture-constrained ecological regions. Specifically, I estimate the following:

Model #2: \[
\ln(\text{Size}_i) = \beta_0 + \beta_1 T_i + \beta_2 P_i + \beta_4 P\text{Anom}_i + \beta_4(P\text{Anom} \times D\text{ry}_i) + \beta_6 \ln(\text{SuppExp}_i) + \beta_6 D\text{ry}_i + \beta_7 Grass_i + \beta_8 Slope_i + \beta_9 Aspect_i + \beta_{10} Elev_i + \sum_j \beta_j USFS_{ji} + \sum_k \beta_k Year_{ki} + u_i \tag{8}
\]

Based on the scientific discussion above, I would expect that changes in\( P\text{Anom} \) would have a greater impact on the size of wildfires in “dry” ecological areas that are moisture-constrained.

1.4.3 Estimator and Choice of Instruments

Estimating these two models requires the use of an instrumental variables estimator, because including suppression effort as an independent variable likely introduces
endogeneity bias. I use a two-stage least squares (TSLS) estimator with heteroskedasticity-robust standard errors. The two instrumental variables that I use are 1) the distance from a fire’s point of origin to the nearest populated area, and 2) whether the area surrounding the fire has been set aside by the U.S. Congress as a designated wilderness (protecting it from human development).

I chose these instruments because I believe they satisfied the two conditions to be a valid instrument: 1) the instrument must be correlated with the endogenous variable, and 2) the instrument must be uncorrelated with the error term in the explanatory equation (in this case $u_i$ in Eq.9). I discuss why these conditions hold for each instrument below.

For distance to the nearest populated area, the first condition is satisfied because there are strong theoretical reasons to suspect that less suppression effort will be applied to fires occurring farther away from populated areas. Specifically, a fire that is farther away from a population center may result in fewer damages, since there would be fewer homes and businesses to destroy. This would lower the marginal benefit of suppression (represented in the model above as a decrease in $X^\text{ND}$) and therefore reduce the optimal level of suppression effort applied. Also, a wildfire that occurs farther away from a population center may be harder for firefighters to access and thus more costly to fight. This would increase the marginal cost of suppression (represented in the model above as an increase in $W^\text{S}$) and therefore reduce the optimal level of suppression effort applied. In either case, the theoretical model predicts that less suppression effort will be exerted in fighting fires that are further
away from population centers. This model prediction can be directly tested by looking at the first-stage results of the two-stage least squares regression.

There are also strong reasons to believe that second condition is satisfied for the distance instrument. This is because the scope for distance to influence wildfire through any pathway other than suppression effort is quite limited. There is no reason to suspect that fires farther away from populated areas face systematically different temperatures or precipitation than fires closer to populated areas. Similarly, there is no reason to suspect that fires farther from populated areas have systematically different topographical characteristics. Therefore, the only path through which distance could directly influence wildfire size is fuel loads. For example, it is possible that fuel loads closer to populated areas are systematically lower because human-caused ignitions in these areas happen more frequently. This is due to the fact more people can visit forests that are closer to population centers, which increases the likelihood of fires being caused by campfire, misplaced cigarettes, arson, etc. Although no study has been conducted on whether fuel loads are systematically different in forests close to population centers, there are two reasons to doubt that more human-caused fires would significantly impact fuel loads of forests included in my analysis. First, human-caused ignitions are much rarer in the western United States, which is the focus of this study, than other parts of the country. Specifically, from 2000-2008, human-caused ignitions accounted for only 35% of total ignitions with an identifiable cause in western USFS regions, compared with 71% in eastern regions (Prestemon et al., 2013). Second, when human-caused wildfires do occur, they tend to be significantly smaller than naturally-caused wildfires, which would
limit their impact on fuel availability. There are three reasons why human fires stay small: 1) they often occur outside the fire season, 2) they occur in vegetation that does not sustain large fires, and 3) they occur in areas where fires are immediately suppressed (Calef et al., 2008). For these reasons, I argue that distance to the nearest population center can be considered exogenous to the size of wildfires included in this analysis. Since this model is overidentified, this claim can be empirically tested using the Hansen J statistic.

For my second instrument, wilderness designation, I argue that the first condition is satisfied because there is a strong theoretical reason to suspect that less suppression effort will be applied to fires occurring in designated wilderness areas. For example, once a portion of public land has been set aside by the U.S. Congress as a designated wilderness it is protected from human development. This means no permanent roads or commercial enterprises, such as mining or timber harvesting, are allowed inside a designated wilderness area. As a result, a fire that occurs in a designated wilderness area would likely result in fewer economic damages, which means the marginal benefit of suppression will be lower (represented in the model above as a decrease in $X^{ND}$) and the optimal level of suppression effort will be lower. Alternatively, a wildfire that occurs in a designated wilderness may be harder for firefighters to access since there are no permanent roads and thus may be more costly to fight. This would increase the marginal cost of suppression (represented in the

---

2 It is important to note that wilderness designation does not influence the types of suppression effort that may be applied in fighting the wildfire. According to a House Committee on Interior and Insular Affairs report “Section 4(d)(1) of the Wilderness Act permits as may be necessary in the control of fire, insects, and diseases This includes the use of mechanized equipment, the building of fire roads, fire towers, fire breaks or fire pre-suppression facilities where necessary and other techniques for fire control. In short, anything necessary for the protection of public health or safety is clearly permissible” (Natural Resources Law Center, 2004).
model above as an increase in $W^S$) and therefore reduce the optimal level of suppression effort applied. In either case, the theoretical model predicts that less suppression effort will be exerted in fighting fires that occur in designated wilderness areas. This model prediction can be directly tested by looking at the first-stage results of the two-stage least squares regression.

In addition, there are also strong reasons to believe that wilderness designation will satisfy the second condition and be uncorrelated with the error term. This is because the scope for wilderness designation to influence wildfire through any pathway other than suppression effort is quite limited. There is no reason to suspect that wilderness areas should face systematically different temperatures or rainfall patterns. Similarly, there is no reason to suspect that wilderness areas should have systematically different topographical characteristics. These are all fixed characteristics of the natural environment that should be unrelated to congressional decision making.

Therefore, the only path through which wilderness designation could directly influence wildfire size is fuel loads. Specifically, by prohibiting economic activities like timber harvesting in these areas, fuel loads could be systematically greater in designated wilderness areas than in non-wilderness areas. Although this is possible, there is reason to believe that such differences would be small. Specifically, timber harvesting on USFS land has fallen dramatically since 1989, in part due to efforts to preserve the habitats of endangered species like the spotted owl (Farnham and Mohai, 1995). Figure 1.3 illustrates the dramatic nature of this decline. As one can see, timber cut volume across the five regions that compose the
western United States fell from 10,000 million board feet in 1987 to less than 1,000 million board feet in 1998. This leads one to suspect that timber harvesting in recent years has not had a significant impact on fuel loads on USFS lands. Therefore, I argue that wilderness designation status can be considered exogenous to the size of wildfires included in this analysis. As stated previously, this claim can be empirically tested using the Hansen J statistic because the model is overidentified.

1.5. Data

The primary data source for this study is the National Interagency Fire Management Integrated Database (NIFMID), which contains data on characteristics of all wildfires controlled by the USFS including the number of acres burned by each fire, the geographic coordinates of the fire’s point of origin, and various measures of the suppression effort that was expended controlling the fire. Although the NIFMID is the best data source for characteristics of wildfires on USFS land, previous analyses have found that the suppression expenditures estimates included in the database cannot always be taken at face value. For example, the Forest Service spent more than $1 billion on suppressing wildfires in FYs 2000 and 2002. Yet, the sum of suppression expenditures for fires included in the NIFMID during those years only totaled $655 and $629 million, respectively (Gebert et al. 2007). This discrepancy was partly driven by the fact that many fires do not have suppression expenditure estimates recorded for them.
Therefore, for purposes of this study, I use a subset of the NIFMID that was used in Donovan et al. (2011). The Donovan et al. dataset only includes data for wildfires occurring between 2003 and 2007 where the USFS was the recorded protection agency or the majority of the acres burned were under USFS jurisdiction and where reasonable estimates of suppression expenditures could be obtained. Specifically, I analyze data for the 466 of these fires that occurred in USFS Regions 1, 3, 4, 5, and 6. I focus on these five regions for two reasons. First, understanding fires that occur in this region would be of greatest interest to policy makers because they account for over 75% of wildfire acres burned between 1978 and 2009. Second, by narrowing my focus to a particular region of the United States, I reduce some of the policy and ecological heterogeneity across fires. The location of each of the 466 fires is illustrated in figure 1.2.

Descriptive statistics for each of the variables included in this study are reported in Table 1.1. Sources and methods for collecting this data are provided below.

1.5.1 Exogenous Variables

Measures of the average temperature and precipitation for the area surrounding each fire were constructed using weather-station level data obtained from the National Climate Data Center from its Global Historical Climatology Network (GHCN) Monthly database. Specifically, I took an inverse-distance weighted average of monthly temperature and precipitation means for every station within 250 miles of a wildfire’s point of origin. I chose

---

3 The GHCN Monthly database includes monthly averages of weather observations from over 70,000 surface stations across the world dating back to the year 1900.
to use an inverse-distance weighted average to reflect the fact that weather conditions closer to a fire’s point of origin are more important to how large that fire will grow than conditions farther away from that point. I chose a radius of 250 miles to make sure that all weather observations that are relevant to a wildfire’s size are included in my estimates. Although the exact radius of 250 miles was arbitrary, it is possible that precipitation that fell many miles from the origin of a fire could still support the growth of fuel surrounding a fire by traveling along streams, rivers, and underground.

Data on whether a fire occurred in a “dry” ecosystem or not was obtained by intersecting the coordinates of a fire’s point of origin with the Ecological Provinces geographic information systems (GIS) layer developed by the USFS ECOMAP Team. A dry ecosystem is defined in this dataset as a region where estimated annual losses of water through evaporation at the earth's surface exceed annual water gains from precipitation.

Data on the topography and other characteristics of the area at each fire’s point of ignition were obtained from NIFMID by Donovan et al. (2011). Specifically, they collected data on the degree of the slope, the aspect, and the elevation at the fire’s point of origin as well as whether the fire occurred in a grassy area or not.

1.5.2. Endogenous and Instrumental Variables
Data on suppression expenditures were obtained from Donovan et al. (2011). These suppression expenditure estimates were adjusted to 2002 dollars using the Consumer Price Index. Data on distance were also obtained from Donovan et al. (2011). Specifically, they calculated distance from each fire to the nearest census-designated place (this is an area of concentrated population, such as towns or cities, which the United States Census Bureau designated for statistical purposes). Data on whether a fire occurred in a designated wilderness area or not was obtained by intersecting the coordinates of each fire’s point of origin with the GIS layer of National Wilderness Areas that was developed by the USFS Automated Lands Program.

1.6. Results

In this section, I present and discuss parameter estimates for the two models developed in Section 1.4. However, before discussing the estimation results, it is instructive to start by looking at some nonparametric evidence to check whether wildfire size appears correlated at all with temperature. Therefore, figure 1.4 plots the natural log of wildfire size against mean temperature in the month the fire occurred. As one would expect, the relationship is positive.

Next, I discuss whether the instruments are valid. As previously discussed, a valid instrument must be correlated with the endogenous variable and uncorrelated with the error term. The first condition can be tested by reviewing first-stage results of the TSLS estimator. The first-stage results for Model 1 including both instruments are reported in column 3 of
Table 1.2. The first-stage results for Model 2 including both instruments are reported in column 3 of Table 1.3. In both models, as theory would predict, suppression expenditures are negatively associated with a wildfire’s distance to the nearest population center in both models. Specifically, in both models, a 10 mile increase in the distance from a fire’s point of ignition to the nearest population center is associated with a 20 percent decrease in suppression expenditures. A t-test indicates this relationship is statistically significant at the 5 percent significance level in both models. Similarly, I find that fires occurring in designated wilderness areas receive less suppression expenditures than those occurring outside such areas. Specifically, suppression expenditures are 32 percent lower for wildfires occurring in wilderness areas.\(^4\) This result is also consistent with the theory outlined above. However, a t-test on the individual coefficient does not show the effect as statistically significant. This is likely due to the fact that distance and wilderness status are correlated (wilderness areas tend to be farther away from populated areas). A joint hypothesis test using the F-statistic reveals that one can reject the null hypothesis both coefficients are zero at the 2 percent significance level in both models.

The second condition of a valid instrument can be tested when a model is overidentified using the Hansen J test. The Hansen J test statistic is asymptotically distributed as a chi-square variable with 1 degree of freedom, which implies a 10% critical value of 2.7. The Hansen J test statistic calculated for Model 1 is 0.23 and the test statistic for Model 2 is

\(^4\) This effect was calculated, based on the reported Model 1 coefficient estimate of -0.41. Because this model takes a log-level functional form, the coefficient estimate must be transformed using the following equation to accurately reflect the partial effect of wilderness status for non-marginal changes: \(\%\Delta y = 100 \times (e^{-0.41} - 1)\).
0.25. As one can see, this implies that I cannot reject the null hypothesis that the instruments are uncorrelated with the error term at any reasonable significance level. Based on these results, I conclude that the instruments being used meet both conditions for validity.

The strength of the instruments is tested using the procedure described in Stock and Yogo (2005). Specifically, they show that the bias of the IV estimator relative to that of the OLS estimator can be tested by comparing the first stage F-test statistic on the excluded instrument to critical values that they calculated. For the purposes of this paper, I use the Stock and Yogo method to test the null hypothesis that the maximum bias of the TSLS estimator relative to the OLS estimator is 20%. Stock and Yogo report that the 5% critical value for this test is 8.75 when there is a single endogenous variables and two instruments or 6.66 when there is a single endogenous variable and only one instrument. I estimate the F-statistic on the excluded instruments for to be 4.89 for Model 1 (see table 1.2, column 3) and 4.81 for Model 2 (see table 1.3, column 3). Because neither F-statistic exceed 8.75, I cannot reject the null hypothesis for either model. This could suggest that weak instrument problems will be present.

One way to mitigate the bias associated with weak instruments is to use just-identified TSLS. As Angrist and Pischke (2008) note, the just-identified IV estimator is median-unbiased and unlikely to be subject to a weak-instruments critique. Therefore, in addition to reporting overidentified TSLS estimates for Model 1 and Model 2, I will also report TSLS estimates where only distance is used as an instrument and where only wilderness status is used as an instrument.
The TSLS results for Model 1 are reported in table 1.4. As expected, I find that fires were larger in areas that had higher temperatures in the month they ignited. Specifically, the results for the overidentified 2SLS model indicate that a 1 degree increase in temperature is associated with a 15 percent increase in wildfire size on average, holding everything else constant. Results for the just-identified models are similar (see column 1 and column 2 of table 1.4).

Also as expected, I find that fires were smaller in areas that had less precipitation in the month the fire was ignited. Specifically, the results for the overidentified TSLS model indicate that a 1 millimeter decrease in total precipitation during the month a fire occurs will increase wildfire size by 32 percent on average, holding everything else constant. This result is consistent with the notion that contemporaneous precipitation levels are most important for fuel flammability. Again, results for the just-identified models are similar.

In addition to the contemporaneous effects of precipitation on wildfire size, we also see that precipitation in previous periods had a significant impact on wildfire size. Specifically, the results for the overidentified TSLS model indicate that a 1 millimeter increase in average precipitation anomaly during the six months prior to a fire will increase wildfire size by 58 percent on average, holding everything else constant. This result is consistent with the notion that heavy precipitation in the months prior to a fire’s ignition can lead to larger wildfires by creating more fine fuels. Again, results for the just-identified models are similar.
The results of Model 2 are reported in table 1.5. As expected, dry ecosystems are much more sensitive to changes in precipitation than non-dry ecosystems. One can see this by looking at the interaction effect between precipitation anomaly and ecosystem type. Specifically, the results for the overidentified 2SLS model indicate that a 1 millimeter increase in the average precipitation anomaly over the 6 months prior to a fire will increase wildfire size by 164% in dry ecosystems as opposed to only 32% in non-dry ecosystems. A joint hypothesis test conducted using the Wald test statistic reveals that this result is significant at the 1% significance level. Results for the just-identified models are similar.

Next I discuss the partial effect of suppression expenditures on wildfire size. The parameter estimates discussed thus far have largely been the same regardless of whether one considered the overidentified model or the just-identified models. This is not true when consider the partial effect of suppression expenditures on wildfire size. Specifically, returning to Model 1, the results for the overidentified 2SLS model indicate that a 1 percent increase in suppression expenditures is associated with a 0.52 percent decrease in wildfire size. By contrast, the model that only uses the wilderness status instrument indicates that a 1 percent increase in suppression expenditures is associated with a .77 percent decrease in wildfire size. And lastly, the model that only uses the distance instrument indicates that a 1 percent increase in suppression expenditures is associated with a .38 percent decrease in wildfire size.

Although none of these coefficient estimates are statistically significant, the estimate for the model only using the distance instrument is likely the preferred estimate. This is the
case for two reasons. First, it is the result of a just-identified model and therefore median-unbiased. Second, the F-statistic from the first-stage results of this model is significantly higher than the F-statistic from the first-stage results of the model only using the wilderness status instrument (see column 1 of table 1.2). In fact, the F-statistic for this model, 6.79, exceeds the previously mentioned Stock and Yogo critical value. Both of these facts suggest that bias associated with weak instruments is less of a problem with this model than any of the others.

In addition to the TSLS estimates of Models 1 and 2, I also provide OLS estimates of each model in table 1.3 in column 2 and 3 respectively. As one can see, the OLS estimates are markedly different from the estimates obtained by TSLS. Specifically, the sign on the coefficient for suppression effort is also positive and strongly significant, which is the opposite of how we would expect suppression to influence wildfire size. Similarly, the wildfire size seems less sensitive to changes in temperature and wildfire size when looking at the OLS estimates than the TSLS estimates. This is not what we would expect from two consistent estimators. A Wu-Hausman test formally confirms that we reject the null hypothesis that the OLS estimates are consistent at the 5% level. This result conforms with the expectation that wildfire size and suppression effort are jointly determined.

1.7. Conclusion
The results presented in this paper can be of great use to USFS policy makers that want to anticipated how higher temperatures from Climate Change will influence wildfire size. For example, according to the PCM-B2 and HadCM3 climate models, temperatures in the western United States are expected to increase between 1.6 C and 6.3 C in the period 2070 to 2100 relative to temperatures in the 1970-2000 period (McKenzie, 2004). Across several different model specification, the results presented in this paper predict that a 1 C increase in temperature will increase mean wildfire size by 13%. Therefore, increase in temperature between 1.6 C and 6.3 C would imply mean wildfire size will increase by 20% to 80%.

To put this into perspective, we can calculate a lower-bound for how much suppression expenditures would have to increase to offset this increase in wildfire size. Specifically, using the preferred model where only the distance instrument is used, we can construct a 95% confidence interval for the population parameter for the coefficient ln(SuppExp) that ranges from -1.24 to 0.47. Using the lower bound of this interval suggests that if the USFS wanted to increase suppression efforts to completely offset an increase in wildfire size of 20-79% they would need to increase suppression expenditures by at least 16-63%. In my dataset, mean suppression expenditures was estimated to be $3.3 million. This means suppression costs on the average wildfire could increase $0.5-$2 million.

It is important to understand the limitations of these results. Specifically, these results hold fuel and ecosystem characteristics constant, when in fact these might change over time. For example, as wildfires become larger, this could result in more fuel
being removed from national forests over the long run, which could mitigate the effects of higher temperatures on wildfire size. Measuring the importance of such changes is beyond the scope of this study, but they do suggest that caution should be taken when using these results to extrapolate impacts of climate changes in the distant future.

1.8. Figures and Tables

Figure 1.1. Illustration of Economic Model

\[ MB = -\frac{\partial ND}{\partial Supp} \]

\[ MC = (W^2) \]
Data Source: Headwater Economics, 2015
Figure 1.2. Total Timber Cut on USFS land by Region 1980-2013
Figure 1.3. Location of Wildfires Included in Dataset
Figure 1.4. Linear Relationships between Mean Temperature and log Wildfire Size
Table 1.1. Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (Hectares)</td>
<td>466</td>
<td>4,082.67</td>
<td>11,183.57</td>
<td>40.46</td>
<td>113,333.70</td>
</tr>
<tr>
<td>T</td>
<td>466</td>
<td>19.36</td>
<td>4.49</td>
<td>1.91</td>
<td>29.42</td>
</tr>
<tr>
<td>P</td>
<td>466</td>
<td>1.57</td>
<td>0.87</td>
<td>0.02</td>
<td>5.19</td>
</tr>
<tr>
<td>P_Anom</td>
<td>466</td>
<td>0.22</td>
<td>0.81</td>
<td>-3.26</td>
<td>3.59</td>
</tr>
<tr>
<td>SuppExp</td>
<td>466</td>
<td>3,366,152.0</td>
<td>7,129,091.00</td>
<td>1,305.31</td>
<td>98,700,000.00</td>
</tr>
<tr>
<td>Dry</td>
<td>466</td>
<td>0.21</td>
<td>0.41</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Grass</td>
<td>466</td>
<td>0.36</td>
<td>0.48</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Aspect</td>
<td>466</td>
<td>-0.13</td>
<td>0.72</td>
<td>-1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Elevation</td>
<td>466</td>
<td>5,284.74</td>
<td>1,971.12</td>
<td>43.00</td>
<td>10,000.00</td>
</tr>
<tr>
<td>Slope</td>
<td>466</td>
<td>38.95</td>
<td>23.93</td>
<td>0.00</td>
<td>150.00</td>
</tr>
<tr>
<td>USFS Region 3</td>
<td>466</td>
<td>0.20</td>
<td>0.40</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>USFS Region 4</td>
<td>466</td>
<td>0.25</td>
<td>0.43</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>USFS Region 5</td>
<td>466</td>
<td>0.20</td>
<td>0.40</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>USFS Region 6</td>
<td>466</td>
<td>0.17</td>
<td>0.37</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2003</td>
<td>466</td>
<td>0.02</td>
<td>0.15</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2004</td>
<td>466</td>
<td>0.15</td>
<td>0.35</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2005</td>
<td>466</td>
<td>0.18</td>
<td>0.39</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>2006</td>
<td>466</td>
<td>0.34</td>
<td>0.47</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Distance</td>
<td>466</td>
<td>15.96</td>
<td>10.61</td>
<td>0.39</td>
<td>70.14</td>
</tr>
</tbody>
</table>
Table 1.2. Results from First-Stage of TSLS Regression for Model 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable: ln(SuppExp)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance</td>
<td>-0.02**</td>
<td>-0.02**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Wilderness Status</td>
<td></td>
<td>-0.50*</td>
<td>-0.41</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.255)</td>
<td>(0.254)</td>
</tr>
<tr>
<td>T</td>
<td>0.10***</td>
<td>0.11***</td>
<td>0.10***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>P</td>
<td>-0.23**</td>
<td>-0.22**</td>
<td>-0.23**</td>
</tr>
<tr>
<td></td>
<td>(0.099)</td>
<td>(0.101)</td>
<td>(0.099)</td>
</tr>
<tr>
<td>P_Anom</td>
<td>0.05</td>
<td>0.02</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.121)</td>
<td>(0.118)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>Dry</td>
<td>-0.43</td>
<td>-0.41</td>
<td>-0.45</td>
</tr>
<tr>
<td></td>
<td>(0.277)</td>
<td>(0.277)</td>
<td>(0.279)</td>
</tr>
<tr>
<td>Grass</td>
<td>-1.32***</td>
<td>-1.34***</td>
<td>-1.35***</td>
</tr>
<tr>
<td></td>
<td>(0.180)</td>
<td>(0.185)</td>
<td>(0.183)</td>
</tr>
<tr>
<td>Aspect</td>
<td>-0.21</td>
<td>-0.24*</td>
<td>-0.21*</td>
</tr>
<tr>
<td></td>
<td>(0.127)</td>
<td>(0.127)</td>
<td>(0.126)</td>
</tr>
<tr>
<td>Elev</td>
<td>0.00*</td>
<td>0.00*</td>
<td>0.00**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Slope</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Constant</td>
<td>12.04***</td>
<td>11.70***</td>
<td>11.98***</td>
</tr>
<tr>
<td></td>
<td>(0.615)</td>
<td>(0.604)</td>
<td>(0.608)</td>
</tr>
<tr>
<td>Observations</td>
<td>466</td>
<td>466</td>
<td>466</td>
</tr>
<tr>
<td>Region Dummies Included</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Dummies Included</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>F-statistic (Weak Instrument Test)</td>
<td>6.79</td>
<td>4.52</td>
<td>4.89</td>
</tr>
<tr>
<td>Hansen J Statistic</td>
<td></td>
<td></td>
<td>0.23</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.233</td>
<td>0.229</td>
<td>0.236</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
### Table 1.3. Results from First-Stage of TSLS Regression for Model 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable:</strong> ln(SuppExp)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance</td>
<td>-0.02**</td>
<td>-0.02**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Wilderness Status</td>
<td>-0.49*</td>
<td>-0.40</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.256)</td>
<td>(0.255)</td>
<td></td>
</tr>
<tr>
<td><strong>T</strong></td>
<td>0.10***</td>
<td>0.10***</td>
<td>0.10***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.021)</td>
<td>(0.020)</td>
</tr>
<tr>
<td><strong>P</strong></td>
<td>-0.24**</td>
<td>-0.24**</td>
<td>-0.24**</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.102)</td>
<td>(0.100)</td>
</tr>
<tr>
<td><strong>P_Anom</strong></td>
<td>-0.03</td>
<td>-0.06</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td>(0.129)</td>
<td>(0.127)</td>
<td>(0.128)</td>
</tr>
<tr>
<td><strong>P_Anom x Dry</strong></td>
<td>0.32</td>
<td>0.32</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>(0.205)</td>
<td>(0.207)</td>
<td>(0.208)</td>
</tr>
<tr>
<td><strong>Dry</strong></td>
<td>-0.44</td>
<td>-0.42</td>
<td>-0.46*</td>
</tr>
<tr>
<td></td>
<td>(0.276)</td>
<td>(0.277)</td>
<td>(0.279)</td>
</tr>
<tr>
<td><strong>Grass</strong></td>
<td>-1.35***</td>
<td>-1.36***</td>
<td>-1.37***</td>
</tr>
<tr>
<td></td>
<td>(0.179)</td>
<td>(0.183)</td>
<td>(0.181)</td>
</tr>
<tr>
<td><strong>Aspect</strong></td>
<td>-0.20</td>
<td>-0.23*</td>
<td>-0.21</td>
</tr>
<tr>
<td></td>
<td>(0.127)</td>
<td>(0.127)</td>
<td>(0.126)</td>
</tr>
<tr>
<td><strong>Elev</strong></td>
<td>0.00*</td>
<td>0.00*</td>
<td>0.00**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td><strong>Slope</strong></td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>12.10***</td>
<td>11.76***</td>
<td>12.03***</td>
</tr>
<tr>
<td></td>
<td>(0.615)</td>
<td>(0.605)</td>
<td>(0.608)</td>
</tr>
</tbody>
</table>

- **Observations** 466
- **Region Dummies Included** Yes
- **Year Dummies Included** Yes
- **F-statistic (Weak Instrument Test)** 6.73
- **Hansen J Statistic** 0.25
- **Adjusted R-squared** 0.234

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
### Table 1.4. TSLS Estimation Results for Wildfire Size Model 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable: ln(Size)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Instrumental Variable: ln(SuppExp)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(SuppExp)</td>
<td>-0.38</td>
<td>-0.73</td>
<td>-0.52</td>
</tr>
<tr>
<td></td>
<td>(0.457)</td>
<td>(0.774)</td>
<td>(0.455)</td>
</tr>
<tr>
<td>T</td>
<td>0.12**</td>
<td>0.16*</td>
<td>0.14**</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.085)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>P</td>
<td>-0.37**</td>
<td>-0.45*</td>
<td>-0.40**</td>
</tr>
<tr>
<td></td>
<td>(0.164)</td>
<td>(0.241)</td>
<td>(0.175)</td>
</tr>
<tr>
<td>P_Anom</td>
<td>0.46***</td>
<td>0.47**</td>
<td>0.46***</td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
<td>(0.198)</td>
<td>(0.175)</td>
</tr>
<tr>
<td>Dry</td>
<td>-0.28</td>
<td>-0.41</td>
<td>-0.33</td>
</tr>
<tr>
<td></td>
<td>(0.413)</td>
<td>(0.542)</td>
<td>(0.439)</td>
</tr>
<tr>
<td>Grass</td>
<td>-1.26*</td>
<td>-1.72*</td>
<td>-1.43**</td>
</tr>
<tr>
<td></td>
<td>(0.644)</td>
<td>(1.026)</td>
<td>(0.637)</td>
</tr>
<tr>
<td>Aspect</td>
<td>0.06</td>
<td>-0.02</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.180)</td>
<td>(0.251)</td>
<td>(0.189)</td>
</tr>
<tr>
<td>Elev</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Slope</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Constant</td>
<td>10.92**</td>
<td>15.05</td>
<td>12.49**</td>
</tr>
<tr>
<td></td>
<td>(5.425)</td>
<td>(9.189)</td>
<td>(5.436)</td>
</tr>
</tbody>
</table>

| Observations   | 466          | 466          | 466          |
| Region Dummies Included | Yes         | Yes         | Yes         |
| Year Dummies Included       | Yes         | Yes         | Yes         |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 1.5. TSLS Estimation Results for Wildfire Size Model 1

<table>
<thead>
<tr>
<th>Instrumental Variable:</th>
<th>Distance Only</th>
<th>Wilderness Status Only</th>
<th>Distance &amp; Wilderness Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(SuppExp)</td>
<td>-0.39</td>
<td>-0.77</td>
<td>-0.50</td>
</tr>
<tr>
<td></td>
<td>(0.461)</td>
<td>(0.807)</td>
<td>(0.461)</td>
</tr>
<tr>
<td>T</td>
<td>0.12**</td>
<td>0.16*</td>
<td>0.13**</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.087)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>P</td>
<td>-0.40**</td>
<td>-0.49*</td>
<td>-0.42**</td>
</tr>
<tr>
<td></td>
<td>(0.171)</td>
<td>(0.258)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>P_Anom</td>
<td>0.30*</td>
<td>0.27</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>(0.177)</td>
<td>(0.216)</td>
<td>(0.190)</td>
</tr>
<tr>
<td>P_Anom x Dry</td>
<td>0.66**</td>
<td>0.78*</td>
<td>0.69**</td>
</tr>
<tr>
<td></td>
<td>(0.331)</td>
<td>(0.437)</td>
<td>(0.349)</td>
</tr>
<tr>
<td>Dry</td>
<td>-0.31</td>
<td>-0.46</td>
<td>-0.35</td>
</tr>
<tr>
<td></td>
<td>(0.417)</td>
<td>(0.562)</td>
<td>(0.445)</td>
</tr>
<tr>
<td>Grass</td>
<td>-1.32**</td>
<td>-1.81*</td>
<td>-1.47**</td>
</tr>
<tr>
<td></td>
<td>(0.655)</td>
<td>(1.084)</td>
<td>(0.654)</td>
</tr>
<tr>
<td>Aspect</td>
<td>0.07</td>
<td>-0.02</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(0.180)</td>
<td>(0.254)</td>
<td>(0.190)</td>
</tr>
<tr>
<td>Elev</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Slope</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Constant</td>
<td>10.24*</td>
<td>14.68</td>
<td>11.51**</td>
</tr>
<tr>
<td></td>
<td>(5.510)</td>
<td>(9.621)</td>
<td>(5.539)</td>
</tr>
</tbody>
</table>

Observations 466 466 466
Region Dummies Included Yes Yes Yes
Year Dummies Included Yes Yes Yes
Wald Statistic (Joint Hypothesis Test) 11.30*** 7.87*** 10.16***

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Table 1.6. OLS Estimation Results for Wildfire Size Models 1 and 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) Model 1</th>
<th>(2) Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(SuppExp)</td>
<td>0.65***</td>
<td>0.64***</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>T</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>P</td>
<td>-0.14*</td>
<td>-0.15**</td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>P_Anom</td>
<td>0.44***</td>
<td>0.36***</td>
</tr>
<tr>
<td></td>
<td>(0.106)</td>
<td>(0.110)</td>
</tr>
<tr>
<td>P_Anom x Dry</td>
<td></td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.203)</td>
</tr>
<tr>
<td>Dry</td>
<td>0.12</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>(0.235)</td>
<td>(0.235)</td>
</tr>
<tr>
<td>Grass</td>
<td>0.08</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.164)</td>
<td>(0.165)</td>
</tr>
<tr>
<td>Aspect</td>
<td>0.30***</td>
<td>0.30***</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Elev</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Slope</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.06***</td>
<td>-1.96***</td>
</tr>
<tr>
<td></td>
<td>(0.710)</td>
<td>(0.712)</td>
</tr>
<tr>
<td>Observations</td>
<td>466</td>
<td>466</td>
</tr>
<tr>
<td>Region Dummies Included</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Dummies Included</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Wald Statistic (Joint Hypothesis Test)</td>
<td>9.42***</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.493</td>
<td>0.495</td>
</tr>
</tbody>
</table>
1.9 References


CHAPTER 2

Has Weed Mobility Created a Tragedy of the Commons Problem that Hastened the Emergence of Glyphosate-Resistant Weeds? Evidence from U.S. Soybean Growers

2.1. Introduction

Glyphosate-resistant (GR) varieties of crops such as soybeans have gained wide acceptance around the world in large part because they are resistant to glyphosate (marketed by Monsanto as “Roundup”), an herbicide that delivers superior weed control combined with low toxicity (Duke and Powles, 2009). According to recent studies, GR crops represent more than 80% of the 120 million hectares of transgenic crops grown annually worldwide (Duke and Powles, 2009). However, the economic viability of GR crop technology is being diminished as glyphosate is becoming less effective in many areas due to the spread of weeds that are also resistant to glyphosate. These GR weeds have emerged because of the selection pressure created by the increased use of glyphosate that accompanied the adoption of GR crops. Data collected by Heap (2012) reveals that GR weed species have been confirmed in 29 states across the U.S. The spread of these glyphosate resistance over the past 10 years is illustrated in Figure 2.1.

This rapid spread of GR weeds has led some to wonder whether policy makers should regulate the weed management practices of U.S. farmers. For example, a 2014 editorial in Nature supported the idea that the U.S. Environmental Protection Agency (EPA) should take
more actions to restrict herbicide use. The authors argued that these actions were warranted, in part, because growers would be reluctant to take steps on their own to avoid resistance because their farms could still “end up infested with weeds from less-assiduous neighbors.”

This argument that weed mobility encourages growers to overuse herbicides has a long history in the theoretical literature (e.g. Regev et al., 1983). The essence of this argument is that when weeds can easily move from one farm to another, the likelihood that GR weeds will infest one grower’s field will not only depend on how much glyphosate he applied to his fields in previous seasons but also how much glyphosate his neighbors applied to their fields. As a result, even if an individual grower reduced his use of glyphosate to lower the risk that his fields will be infested with GR weeds in the future, his actions may not actually reduce his risk unless his neighbors reduce their use of glyphosate as well.

Theoretically, weed mobility creates a “tragedy of the commons” problem, where susceptibility of a weed population to glyphosate is an open access resource that growers overuse when they cannot coordinate their efforts. Although this hypothesis is plausible and consistent with natural resource theory, very little empirical work has been conducted to determine whether a “tragedy of the commons” problem actually exists in this context. This is important because this argument is conditional on growers not being able to coordinate their efforts to avoid glyphosate overuse, even though this type of coordination has been used to voluntary solve common property resource problems in the past (see Ostrom et al., 1994).

The only study that has empirically investigated whether weed mobility has affected herbicide use was Clark and Carlson (1990), which could find no evidence that herbicide susceptibility exhibit common property characteristics. However, that does not mean that this conclusion is still true of glyphosate susceptibility today. Not only was this study conducted before the introduction of GR crop technology, it only considered an aggregate of all herbicides applied by all farmers. New analysis is needed to answer the question of whether a “tragedy of the commons” problem hastened the emergence of GR weeds.

The goal of this paper is to fill this gap in the literature by empirically testing whether weed mobility has led soybean growers to overuse glyphosate. To accomplish this goal, I derive a set of testable predictions from a simple game theoretic model of herbicide applications. Specifically, the model predicts that weed mobility has the most impact on growers’ incentives when they are located close to one another. As the number of neighbors surrounding a grower increases, the less likely it is that his individual efforts to avoid glyphosate resistance by using less glyphosate will matter (in the absence of cooperation). The hypothesis that glyphosate application rates are positively related to neighbor density is then empirically tested using 2006 field-level data for soybean growers.

The remainder of the paper is organized as follows. First, I discuss the scientific literature on the nature of weeds, how they are managed, and how they develop herbicide resistance. Second, I intuitively discuss the implications of weed mobility on herbicide use. Third, I present a more formal game theoretic model of how growers make herbicide application decisions in the presence of weed mobility. Next, I empirically test the
predictions of this model using field-level data from the Agricultural Resource Management Survey. The paper concludes with a discussion of these results and their implications for policy makers.

2.2. Background

The Weed Science Society of America defines a weed as a plant growing where it is not desired (Zimdal, 1999). This definition makes it clear that what distinguishes weeds from other plants is their relation to the goals of human beings. Therefore, this distinction is quite subjective. For example, a homeowner that wants to maintain a picturesque lawn filled with Kentucky Bluegrass would view dandelions in his lawn as weeds. By contrast, a homeowner that enjoyed eating dandelion greens may view dandelions in his lawn as a blessing.

In the context of row crop farming, profit-maximizing farms would identify plants that reduce crop yields as weeds. The extent of crop yield loss is closely tied to weed density (i.e. the number of weeds per row or per acre). Generally, a higher weed density is associated with a greater yield loss because more weeds means more competition for nutrients, water, light, and other resources that crop plants need to grow. (see Aldrich & Kremer, 1997).\(^6\)

In order to mitigate the damages created by weeds, growers can reduce weed density by using a number of weed control techniques. The most important of these techniques is

\(^6\) Other factors besides weed density also influence crop yields, such as when the weeds are present in relation to the life cycle of the crop. However, weed density is considered the most important factor, while other factors only modify the impact of weed density (Aldrich & Kremer, 1997).
applying herbicide to problem plants. However, over reliance on one herbicide can ultimately lead to weeds becoming resistant to that herbicide. In the following sections, I describe each of the techniques growers can employ to control their weed problem and the mechanism for how herbicide-resistance develops. This discussion will inform the economic model and empirical strategy that I discuss later in the paper.

2.2.1 Weed Control Methods

Soybean growers have many ways of controlling weeds. First, growers can work to prevent weeds from infesting their fields to begin with. This type of weed prevention primarily focuses on keeping weed seed out of one's field. For example, farmers can use crop seed that has been processed to ensure they are not contaminated with weed seed. Similarly, farmers can clean their combines, cultivators, and other equipment after they are used to keep from spreading weed seeds that may have clung to this equipment during use (Aldrich & Kremer, 1997).

If prevention measures were completely successful, then this would solve a farmer's weed problem. However, this will never be the case and growers must take further steps to control weed infestations and minimize their damage. These steps can be separated into three main categories: mechanical control techniques, cultural control techniques, and chemical control techniques (Aldrich & Kremer, 1997). Mechanical control techniques are any physical method used to control weed infestations. The most common form of mechanical control is tillage, which controls weeds by burying them and separating the shoots of the
weed from its roots. However, there are many other mechanical control techniques that could also be used such as hand pulling and controlled burning (Zimbdal, 1999).

Cultural control techniques involve changing crop production practices to make field conditions more favorable for crop growth and less favorable for weeds. For example, reducing the space between crop rows can help control weed infestations by giving weeds less room to grow and shading them from the sun. Similarly, crop rotation has been shown to reduce weed infestations. This is because some weeds associate with certain crops more than others. Therefore, when one crop is grown for many years (a monoculture), there is a potential for weeds associated with this crop to become established in the soil. Crop rotation works to discourage this by creating an unstable and frequently inhospitable environment that prevents the proliferation of a particular weed species (Aldrich & Kremer, 1997).

Lastly, chemical control techniques involve the use of chemicals that kill or alter the growth of weeds. These chemicals are known as herbicides. Although mechanical and cultural control techniques are still widely used today, herbicide use began to replace these practices as the primary weed control method for soybeans in the 1960's (Fernandez-Cornejo et al., 2014). From 1966 to 1990, the percentage of U.S. soybean acres treated with herbicides increased from 27% to 95%.

Herbicide use has only grown more important to soybean growers with the introduction of soybeans genetically modified to be resistant to glyphosate, a broad spectrum herbicide, in 1998. Glyphosate-based herbicides all work on the same biochemical principle - they inhibit a specific enzyme that plants need in order to grow. The specific enzyme is
called EPSP synthase. Without that enzyme, plants are unable to produce other proteins essential to growth, so they yellow and die over the course of several days or weeks. A majority of plants use this same enzyme, so almost all plants succumb to glyphosate (Powels et al., 1998).

How much glyphosate needs to be applied to achieve the desired level of weed control depends on a variety of factors. For example, cold temperatures and high precipitation can both work to make glyphosate less effective. However, controlling for these factors, glyphosate seems to exhibit decreasing returns to scale. For example, data from four separate single-dose experiments measuring the effects of glyphosate on a non-GR population of rigid ryegrass (a specific species of weed) suggests that approximately 123 grams of active ingredient per hectare are required for 50% mortality of that population. However 450 grams of active ingredient per hectare are required to achieve close to 100% mortality (Powels et al., 1998). In other words, doubling the glyphosate input does not double the fraction of population controlled.

2.2.2 Herbicide Resistance

Herbicide resistance is defined by the Weed Science Society of America as the inherited ability to survive an herbicide application that would normally be lethal to the wild variety of the plant (Zimbdal, 1999). By this definition, herbicide resistance is a genetic trait that occurs naturally in some individual members of particular weed species. However, the fraction of a given weed population that shares this herbicide resistance trait can grow
through the process of natural section. For example, although Glyphosate is a broad-spectrum herbicide that is designed to kill a large variety of weed species, some members of each species can possess a genetic trait that enables them to survive a typical glyphosate treatment. As a result, if a grower only manages the weeds in his field using glyphosate, he is creating conditions where weeds that have the resistance trait are more likely to reproduce than weeds without the trait. Over several generations, this will lead to a larger fraction of the weed population that exhibits glyphosate resistance.

The recent history of glyphosate use provides a clear example of how continued use of a single herbicide can lead to the emergence of weeds resistant to that herbicide. Specifically, between 1995 and 2006, the mean rate of glyphosate application per acre has increased 31% (Benbrook, 2012). Similarly, the fraction of soybean acres using glyphosate increased to over 80% during the same period, but has declined since (see Figure 2.2).

Lastly the number of herbicides with different active ingredients or different modes of action used on at least 10% of soybean hectares has fallen overtime (see Figure 2.3). As expected, this reliance on glyphosate as the primary chemical technique for controlling weeds led to the emergence of glyphosate resistant weeds. In 2001, a glyphosate-resistant strain of Conyza Canadensis (a.k.a. horseweed) became the first GR weed identified on a GR soybean crop in the US (Van Gessel, 2001).

It is tempting to infer from this discussion that soybean growers “overused” glyphosate. However, in order to make this kind of statement one must define what one means by “overuse.” From the traditional welfare economics perspective, a grower would
only be overusing glyphosate if the marginal social costs exceeded the marginal social benefit. In the next section, I discuss the economic reasoning for why weed mobility may lead soybean growers to overuse glyphosate according to this definition.

2.3. Weed Susceptibility as a Common Property Resource

Based on the discussion in the previous section, it is clear that an herbicide will become less effective because continually using it encourages the emergence of herbicide-resistant weed populations through a process of natural selection. As a result, many economists have conceptualized the susceptibility of weeds to herbicides as a finite resource that is exhausted through its continual use (e.g. Hueth and Regev, 1974).

How quickly firms in a competitive market will exhaust a finite resource and whether that extraction rate is socially optimal depends in large part on whether the resource is considered private or common property. In the case where a resource is private property a firm can exclude rivals from using that resource. As a result, he bears the full opportunity cost associated with his resource use. For example, if a firm owned a private aquifer, then every gallon of groundwater he chose to pump today would be a gallon he could not pump tomorrow. As Hotelling (1931) was able to theoretically show, the incentives created by having property rights over a resource will lead firm operating in a competitive output market to maximize net social benefits (ignoring potential environmental costs associated with extraction).
However, a firm’s incentives change dramatically when a resource is common property and he cannot exclude rivals from using it. In that case, a firm no longer bears the full opportunity cost associated with his choices. For example, if a firm using an open access aquifer chooses to pumps a gallon today, it is not clear that he is actually giving up a gallon he could have pumped tomorrow, because a rival might have extracted that gallon of water instead. As a result, firms are encouraged to extract water more quickly than before because the opportunity cost of pumping a gallon of water today is lower under common property (Miranowski and Carlson, 1986).

The way that the presence of rival firms can influence the opportunity cost of exploiting a resource is sometimes referred to as a “strategic externality.” Negri (1989) provides the following intuitive summary of this externality in the context of groundwater:

“The strategic externality has an intuitive interpretation in the aquifer context. With property rights undefined and access nonexclusive, the ”rule of capture” governs the ”ownership” of the reserve stock. The rule of capture grants farm operators exclusive rights to that portion of the ground-water that they pump. What an operator does not withdraw today will be withdrawn, at least in part, by rival farms. The fear that farmers cannot capture tomorrow what they do not pump today undermines their incentive to forgo current pumping for future pumping.” (emphasis added p.9)

Some economists have argued that a strategic externality like this could exist in the context of pesticide application if the pest is highly mobile (Regev et al., 1983). When weeds are highly mobile, the individual weeds that a grower finds in his fields are just members of a larger weed population that may span many square kilometers and include the fields of other farms. This means that the seeds of GR weeds that emerge in the field of a grower that relied
heavily on glyphosate can travel and ultimately appear in the field of a grower that never used glyphosate. As a result, how quickly the glyphosate susceptibility of this highly mobile weed population is exhausted depends on how much glyphosate is applied by all growers using glyphosate in the area. This means that an individual grower has less incentive to reduce use of glyphosate today to avoid the emergence of glyphosate resistance in the future because his neighbors may cancel out his efforts by using more glyphosate.

So are weeds mobile enough to make strategic externalities a concern? Although weed mobility is difficult to measure, there is clear evidence in the weed science literature that some weed species are relatively mobile and can disperse their seeds over great distances. For example, the seeds of the Conyza Canadensis plant (the first weed species affecting soybean growers to acquire glyphosate resistance) can travel up to 547 yards on the wind alone (Dauer et al., 2007). Seeds can travel even farther if they are carried by streams or become attached to animals, humans, or farm equipment (Zimbdal, 1999).

So weeds are certainly mobile, but do farmers recognize this in their decision making? There is some indirect evidence to suggest that they do. Specifically, a 2012 USDA survey asked soybean growers if they believed “the glyphosate management practices [they] used would be more effective if operators of nearby farms also used them” (Livingston, 2013). Over half of the respondents said yes. Figure 2.4 reports the results of this survey by USDA Farm Production Region—regional classifications created by the USDA to divide the United States into regions that reflect geographic specialization in the production of farm commodities.
Note that many more respondents in the Appalachian region, which is comprised of Kentucky, North Carolina, Tennessee, Virginia, and West Virginia, said that the effectiveness of their efforts to manage glyphosate resistance depended on the actions of their neighbors than in any other region. This is interesting because farms appear to be densely placed in the Appalachian region than the rest of the United States. According to data collected from the 2007 Agricultural Census, the mean density of farms with cropland across all counties in the United States is 1.4 farms per 1,000 acres. By contrast, the mean density of farms with cropland in counties inside the Appalachian Region is 1.98 farms per 1,000 acres. The distribution of county farm densities is illustrated in Figure 2.7.

Taken together, this evidence seems to support the argument that the glyphosate susceptibility of weeds can be viewed as a common property resource. However, this on its own cannot be taken as conclusive evidence that glyphosate was overused in the social welfare sense discussed above. This is because even if weed susceptibility is a common property resource, it is possible that individual soybean growers coordinated with one another to avoid overusing glyphosate. Although I could not identify any direct evidence that a Coasean bargain took place among farmers in the context of weed management, there are numerous examples of economic agents voluntarily coordinating with one another to manage similar types of open access resource problems (Ostrom et al., 1994).

To determine whether a strategic externality led to an overuse of glyphosate, I develop a model of how soybean growers would act in the presence of this externality and derive predictions from that model that can be tested empirically.
2.4. A Simple Game Theoretic Model of Herbicide Application

For the purposes of this study, I model herbicide applications as a static simultaneous game among n players that face a highly mobile weed population. I choose to model this as a simultaneous game in order to avoid the possibility of players coordinating their herbicide application efforts (an Ostrom-type solution). Also, I choose to ignore intertemporal dynamics by assuming that growers only maximize profit over 2 periods. This allows me to avoid modelling this as a dynamic game because the grower has no strategic concerns in the second/final period--he will simply apply glyphosate until the marginal benefit in the second period is equal to the marginal cost in the second period. As a result, a two-period game collapses into a single-period game.

The remainder of this section continues as follows. First, I define a payoff function for an individual grower—grower i. Second, I use that payoff function to derive a best-response function for that grower. Lastly, I consider a Nash Equilibrium with n players where each grower has an identical best response function. In each step where I must choose a specific functional form, I choose the one that makes analytical consideration of equilibrium easier. However, in each case, I discuss how the general characteristics of the functional form I chose are consistent with assumptions required by the weed science literature reviewed in Section 2.2.
2.4.1 Define the Payoff Function

Suppose that a soybean grower owns a one-acre farm that can produce a maximum of \( Y_t \) units each period, which can be sold at market for \( p \) dollars per unit. However, some percentage of the maximum output maybe destroyed by weeds before it is harvested. This percentage is determined by \( D(W_t) \), a damage function that relates the weed density (the number of weeds per acre that are present in the field at the end of period \( t \)), \( W_t \), to the fraction of output destroyed.\(^7\) Weed density can be reduced by the application of glyphosate \((g_t)\), which can be purchased at price \( q \). Therefore, the grower’s problem is to choose the glyphosate application rate that maximizes the present value of profits:

\[
Π = \left[pY_1 \left(1 - D(W_1(g_1))\right) - qg_1\right] + \beta \left[pY_2 \left(1 - D(W_2(g_2))\right) - qg_2\right]
\]  

(1)

To carry this analysis further, we must specify the damage function \( D(W_t) \). Specifically, I assume that the fraction of output destroyed is proportional to the density of weeds present in the field at the end of period \( t \):

\[
D(W_t) = \phi W_t(g_t)
\]  

(2)

where \( \phi \) is a parameter. As one can see, a higher weed density will be associated with a greater loss in output, which is consistent with the weed science literature reviewed in Section 2.2.

As mentioned above, weed density at the end of each period depends on how much glyphosate \((g_t)\) is applied by the grower. However, as previously discussed in Section 2.2, not

\(^7\) To introduce the damage that weeds cause to GR-corn yield, I use an approach similar to the damage control model introduced by Lichtenberg & Zilberman (1986).
all members of a weed population are equally vulnerable to glyphosate. Suppose, for
simplicity, that some of the weeds in a grower’s field are vulnerable to glyphosate (W_v) and
some are entirely resistant to glyphosate (W_r). The number of weeds present in the field after
glyphosate has been applied will be determined by the following:

\[ W_t = W_v \left(1 - \ln \left( \frac{g_t}{g_{\text{max}} e} \right) \right) + W_r; \quad \frac{g_{\text{max}} e}{e} \leq g_t \leq g_{\text{max}} \] (3)

where \( g_{\text{max}} \) is the amount of glyphosate that will eradicate all vulnerable weeds in the
farmer’s field. Note that I multiply \( g_t \) by \( \frac{e}{g_{\text{max}} e} \) and restrict its values to fall between \( \frac{g_{\text{max}}}{e} \leq g_t \leq g_{\text{max}} \) to ensure that the product of \( \ln \left( \frac{g_t}{g_{\text{max}} e} \right) \) falls between 0 and 1. Although this
specific functional form was chosen for analytical convenience, its basic characteristics are
consistent with how I described the impacts of glyphosate application on weed density in
Section 2.2. Specifically, this functional form exhibits decreasing returns to scale with
glyphosate application so that a decreasing percentage of weeds is destroyed as more
glyphosate is applied to the field.

Next I impose a resource constraint so that the fraction of weeds that are vulnerable to
glyphosate decrease as more glyphosate is applied. I impose this constraint by first assuming
that a fixed number of weeds appear in the farmer’s field each period (W_0) and that some
percentage of these weeds will be resistant to glyphosate and some will be vulnerable. Next, I
assume the percentage of GR-weeds appearing in a field is increasing in the sum of
glyphosate applied by all farmers in the community in the previous period. Specifically, I assume:

\[ W_r = W_0 \left( \ln \left( \frac{G_{t-1}}{G_{stock}} e \right) \right); \frac{G_{stock}}{e} \leq G_{t-1} \leq G_{stock} \]

(4)

where \( G_{stock} \) is the initial stock of glyphosate susceptibility in the weed population that is exhausted through the cumulative glyphosate use of soybean growers and \( G_{t-1} \) is the sum of all growers glyphosate applications in the time period t-1. Specifically, if there are \( n \) farmers, then \( G_{t-1} \) is defined as \( G_{t-1} = \sum_{i=1}^{n} g_{i,t-1} \). Note that I multiply \( G_{t-1} \) by \( \frac{e}{G_{stock}} \) and restrict its values to fall between \( \frac{G_{stock}}{e} \leq G_{t-1} \leq G_{stock} \) to ensure that the product of \( \ln \left( \frac{G_{t-1}}{G_{stock}} e \right) \) falls between 0 and 1. Although this is an arbitrary functional form that was chosen for analytical convenience, its basic characteristics are consistent with how I described the emergence of glyphosate resistance in earlier sections. Specifically, as more glyphosate is collectively applied (\( G_{t-1} \) increases), the stock of glyphosate susceptibility will be depleted and the fraction of resistant weeds will increase. If enough glyphosate is applied such that \( G_{t-1} = G_{stock} \), then all susceptibility will be exhausted and 100% of the weeds that appear in a grower’s field will be resistant to glyphosate.

Since, by definition, the sum of \( W_r \) and \( W_v \) must equal \( W_0 \), this implies the number of weeds that are vulnerable to glyphosate each period will be \( (W_0 - W_r) \) or more specifically:
\[ W_v = W_0 \left( 1 - \ln \left( \frac{G_{t-1}}{G_{stock}} e \right) \right) \] (5)

Substituting these expressions for \( W_v \) and \( W_r \) into Eq. 5 yields

\[ W_t = \left[ W_0 \left( 1 - \ln \left( \frac{G_1}{G_{stock}} e \right) \right) \left( 1 - \ln \left( \frac{g_1}{g_{max} e} \right) \right) \right] + \left[ W_0 \left( \ln \left( \frac{G_1}{G_{stock}} e \right) \right) \right] \] (6)

Substituting this expression for \( W_t \) into the damage function and substituting the damage function back into the two period profit function yields this payoff function for farmer \( i \):

\[
\Pi = \left[ pY_1 \left( 1 - \phi \left( W_0 \left( 1 - \ln \left( \frac{g_1}{g_{max} e} \right) \right) \right) \right) - q g_1 \right] + \\
\beta \left[ pY_2 \left( 1 - \phi \left( \left[ W_0 \left( 1 - \ln \left( \frac{G_1}{G_{stock}} e \right) \right) \left( 1 - \ln \left( \frac{g_2}{g_{max} e} \right) \right) \right] + \left[ W_0 \left( \ln \left( \frac{G_1}{G_{stock}} e \right) \right) \right) \right) - q g_2 \right] \]
\] (7)

2.4.2 Derive Best Response Function

Using this modified profit equation, we can find the best response function for farmer \( i \) by taking the first derivative with respect to \( g_1 \) and \( g_2 \) and setting these derivatives equal to zero \( \left( \frac{\partial \Pi}{\partial g_1} = 0, \frac{\partial \Pi}{\partial g_2} = 0 \right) \). These first order conditions are:

\[
\frac{\partial \Pi}{\partial g_1} = 0 \Rightarrow pY_1 \frac{\phi W_0}{g_{max} e} - q - \beta pY_2 \phi W_0 \frac{\ln \left( \frac{g_2}{g_{max} e} \right)}{G_1} = 0 \] (8)
\[ \frac{\partial \Pi}{\partial g_2} = 0 \Rightarrow \frac{\beta p Y_2 \phi W_0}{g_2^{\text{max}e}} - \frac{\beta \phi W_0 \ln \left( \frac{g_1}{g_2^{\text{max}e}} \right)}{g_2^{\text{max}e}} - \beta q = 0 \quad (9) \]

Solving Eq.9 for \( g_2 \) yields

\[ g_2 = \frac{g_2^{\text{max}e} \phi W_0 (p Y_2 - \ln \left( \frac{g_1}{g^{\text{stock}e}} \right))}{q e} \quad (10) \]

Substituting this back into Eq.10 yields the following profit maximization condition for applying glyphosate in period 1.

\[ q = \frac{p Y_1 \phi W_0}{g_1^{\text{max}e}} - \beta \left( \frac{p Y_2 \phi W_0 \ln \left( \frac{\phi W_0 (p Y_2 - \ln \left( \frac{g_1}{g_2^{\text{max}e}} \right))}{q} \right)}{g_1} \right) \quad (11) \]

As a result, we arrive at the intuitive conclusion that the grower will apply glyphosate until the “net” marginal benefit equals the marginal cost. Specifically, the net marginal benefit is the marginal benefit of applying glyphosate today \( \left( \frac{p Y_1 \phi W_0}{g_1^{\text{max}e}} \right) \), minus the discounted value of the lost vulnerability next period \( \left( \beta \left( \frac{p Y_2 \phi W_0 \ln \left( \frac{\phi W_0 (p Y_2 - \ln \left( \frac{g_1}{g_2^{\text{max}e}} \right))}{q} \right)}{g_1} \right) \) ). The marginal cost of glyphosate is the price \( (q) \).
2.4.3 Symmetric Nash Equilibrium

At this point we assume the equilibrium glyphosate application rate across all farmers is symmetric and that each of the other \( n \) farmers in the community that faces a shared weed population will apply the same amount of glyphosate to his field.

\[
q = \frac{pY_2 \phi W_0}{g_{max}} - \beta \left( \frac{pY_2 \phi W_0 \ln \left( \frac{\phi W_0 \left( pY_2 - \ln \left( \frac{n g_1}{g_{stock}} \right) \right)}{q} \right)}{n g_1} \right)
\]  \hspace{1cm} (12)

Taking the limit of this expression as \( n \) goes to infinity yields the following result:

\[
\lim_{n \to \infty} q = \lim_{n \to \infty} \left( \frac{pY_2 \phi W_0}{g_{max}} \right) + \lim_{n \to \infty} \beta \left( \frac{pY_2 b W_0 \ln \left( \frac{\phi W_0 \left( pY_2 - \ln \left( \frac{n g_1}{g_{stock}} \right) \right)}{q} \right)}{n g_1} \right)
\]  \hspace{1cm} (13)

This yields the following result:

\[
q = \frac{pY_2 \phi W_0}{g_{max}}
\]  \hspace{1cm} (14)

As \( n \) approaches infinity, the “net” marginal benefit of applying glyphosate increases. In fact, as \( n \) becomes very large, the “net” marginal benefit of applying glyphosate today tends to the level we would observe if the farmer did not consider the future damages from applying glyphosate (i.e. where \( \beta=0 \)).
2.4.4 Testable Predictions

First, when weeds are mobile and the number of neighbors surrounding a grower \( n \) is very large it will appear as though the grower is not discounting the future \( (\beta=0) \). Therefore, one could possibly determine if glyphosate is being overused by econometrically estimating the discount factor and testing whether it is significantly different from zero. This is the approach taken by Clark and Carlson (1990). However, there are several limitations with this approach. First, this approach doesn’t allow the researcher to distinguish between the hypothesis that weed susceptibility is a common property resource and the hypothesis that soybean growers are myopic and truly have a discount factor close to zero. Second, the discount factor will only approach zero in the limit as the number of neighbors approach infinity. As a result, it is possible that growers that are not surrounded by a large number of neighbors may have a discount factor greater than zero, but they may still be overusing glyphosate.

An alternative prediction of this model that one could test is that strategic externalities will lead the equilibrium rate of resource extraction (i.e. the glyphosate application rate) to increase as the number of neighbors surrounding exploiting a resource increases. Similar predictions have been derived from other game theoretic models of resource extraction. Examples of papers that include such models are Provencher and Burt (1993) and Brooks et al. (1999), although neither article tests this prediction empirically.

This prediction suggests that a potential test for the presence of strategic externalities could be phrased as the following hypothesis test:
If the null hypothesis is rejected, I would take this as evidence that a strategic externality exists that may have led soybean growers to overuse glyphosate. However, if the null hypothesis is not rejected, this does not mean that strategic externalities do not exist or that it was internalized through a process of Coasean bargaining. It is important to note that in this model I have considered the strategic externality as being the only relevant spillover from having more neighbors. In reality, having more neighbors could have its benefits that were not considered here. For example, having more neighbors may help spread information about effective herbicide practices, which could potentially help growers use less glyphosate. Therefore, a failure to reject the null hypothesis could suggest that information spillovers simply dominated the strategic externality. In the next section, I describe the econometric approach that I use to empirically perform this hypothesis test.

2.5. Estimating the Partial Effect of Neighbor Density on Glyphosate Application Rates

I investigate the partial effect of having more neighbors on glyphosate application rates \( \frac{\partial g}{\partial n} \) by estimating a single-equation specification of glyphosate demand using cross-sectional data collected from the 2006 USDA Agricultural Resource Management Survey (ARMS) of U.S. soybean growers. I use a single-equation approach because I am relying on cross-sectional data and I assume that soybean growers are small actors in a global market who face the same prices for their inputs and outputs. If this assumption is correct, it would
imply that differences in glyphosate application rates across respondents should only differ by differences in the “net” marginal benefit of glyphosate application (as illustrated in Figure 2.5), which depends on soil, weed type, etc. Unfortunately, this assumption could not be readily empirically tested because ARMS does not require respondents to report input or output price information. A more detailed discussion of the ARMS dataset is provided in the next section.

In order to estimate the demand equation for glyphosate, I must choose which variables to include in the estimated model, the parametric functional form that will be used, and select an estimator to estimate the parameters themselves.

2.5.1 Included Variables

In terms of which variables to include in the estimated model, this question is largely answered by the discussions in Section 2.2 and Section 2.3. However, some of the variables included in the economic model could not be included in this study model due to data limitations, so I had to use suitable proxies.

Specifically, the actual number of neighbors surrounding a soybean grower that face the same weed population cannot be observed. This is because the size and shape of weed populations is unknown. For the purposes of this study, I make the simplifying assumption that weed populations are divided by county lines. Therefore, the number of relevant neighbors can be obtained by simply counting the number of farming using glyphosate in each county. Unfortunately, that information is also not available. Instead, since glyphosate is
widely used across many types of crops, I use the number of farming operations with cropland as a proxy. To control for differences in county size, I divide the number of number of farms by the number of acres of each county. I refer to the resulting ratio of farming operations to county acres as the “neighbor density”.

In addition to neighbor density, I also control for other factors that influence the marginal benefit of glyphosate application. For example, I control for size of operation (as this may influence production practices). Also, I control for weather conditions because they can influence the effectiveness of glyphosate. Similarly, I control for whether a grower pursued other weed management techniques that might influence the marginal benefit of glyphosate by changing the quantity of weeds that would have to be controlled by glyphosate. Specifically, I control for whether growers utilized tillage methods (which should decrease the pre-application weed density) and whether growers practiced crop rotation (which also decrease weed density).

Lastly, I include controls for the USDA Farm Production Region the grower is located to capture unobservable factors that may influence glyphosate applications and vary geographically. As mentioned earlier, Farm Production Regions are regional classifications created by the USDA to divide the United States into regions that reflect geographic specialization in the production of farm commodities. Figure 2.6 illustrates the regions.
2.5.2 Functional Form

A level-level functional form was chosen for this model specification because Ramsey’s (1969) regression specification error test could not reject the null hypothesis that there was no specification error at the 5% level. A test of the log-log functional form did reject this hypothesis. Specifically, I estimate the following base model:

\[ Gly_i = \beta_0 + \beta_1 N_i + \beta_2 N_i^2 + \beta_3 Size_i + \beta_3 T_i + \beta_4 P_i + \beta_5 Row_i + \beta_4 No\_Till_i + \beta_5 Crop\_Rot_i + \sum_j \beta_j USDA_{ji} + u_i \]  

(15)

The variables are defined as follows:

- \( Gly_i \) = grower i’s post-emergence glyphosate application rate (lbs. per acre),
- \( N_i \) = the number of farms per 1,000 acres in the county containing grower i,
- \( Size_i \) = number of acres grower i devotes to soybean production,
- \( T_i \) = average 2006 spring temperature for the county surrounding grower i,
- \( P_i \) = total 2006 spring precipitation for the county surrounding grower i,
- \( Row_i \) = average row width of soybeans in grower i’s field,
- \( Crop\_Rot_i \) = dummy variable equaling 1 when grower rotated his/her crops,
- \( No\_Till_i \) = dummy variable equaling 1 when grower used no tillage practices,
- \( USDA_{ji} \) = dummy variable equaling 1 when grower i located in USDA region j,
- \( u_i \) = disturbance term.
In addition to estimating this base model, I also estimate a model where the variable for neighbor density is interacted with the categorical variable for the Appalachian USDA Production Region (indicated below as $App_i$). Specifically, I estimate the following:

$$Gly_i = \beta_0 + \beta_1 N_i + \beta_2 N_i^2 + \beta_1 (N_i \times App_i) + \beta_2 (N_i^2 \times App_i) + \beta_3 Size_i + \beta_5 T_i + \beta_4 P_i + \beta_5 Row_i + \beta_4 No\_Till_i + \beta_5 Crop\_Rot_i + \sum_j^9 \beta_j USDA_{ji} + u_i$$  \hspace{1cm} (16)

I estimate this model because, as discussed in Section 2.2, neighbor densities appear to be greater in this region compared with other regions in the United States. As a result, one would expect strategic externalities to be a greater problem for growers in the region.

In addition to these two model specifications, I also report results for estimating each of these models excluding controls for row width, tillage practices, and crop rotation practices. This is done as a robustness check as it could be argued that a forward-looking grower would choose production practices and herbicide applications as part of the same dynamic optimization problem. Therefore, I consider results where these variables are excluded to avoid problems with endogeneity bias.

2.5.3 Estimator and Hypothesis Test

I estimate the models listed above using Ordinary Least Squares (OLS) with robust standard errors. After estimating this model, I perform the relevant hypothesis test by considering the partial effect of neighbor density on glyphosate application rates. Specifically, if the glyphosate application rate is increasing with the neighbor density
surrounding a grower, this would be evidence that externalities are a driving factor in glyphosate application decisions. Therefore we would seek to test the following hypotheses:

\[ H_{null}: \frac{\partial G}{\partial N} = (\beta_1 + 2\beta_2 N_i) = 0 \]

\[ H_{alt}: \frac{\partial G}{\partial N} = (\beta_1 + 2\beta_2 N_i) > 0 \]

This test can be performed for a given neighbor density using a standard one-sided t-test.

2.6. Data

The primary data source for this study is field-level data on production practices for over 2,000 soybean growers in the United States. This data was collected by the USDA as part of Agricultural Resource Management Survey (ARMS), a cross-sectional survey that is conducted at irregular intervals for different commodities. In the case of Soybeans, recent surveys were conducted in 2000, 2002, 2006, and 2012. However, only national-level data is consistently reported for each of these years. This is because the sampling procedure used in these surveys was not intended to support State- or county-level estimates.\(^8\) As a result, a panel dataset cannot be constructed. Instead, for the purposes of this study, I have chosen to focus on the microdata from a single cross section.

Specifically, in this analysis I use field-level data collected from soybean growers during 2006 ARMS. I chose to use data collected from the 2006 ARMS to avoid concerns that growers may not have been informed about the connection between glyphosate use and

---

\(^8\) Sufficient data was ultimately obtained for some States such that USDA could report estimates on various production practices like herbicide applications. However, which States the USDA reports estimates for changes for each year the survey was conducted. County-level data are not publicly available for any year.
the emergence of glyphosate resistance. Although I could not identify an objective measure of whether soybean growers understood this connection or not, it seems unlikely that many soybean growers were ignorant of the dangers of glyphosate resistance in 2006. Not only had some weed scientists been predicting the potential emergence of glyphosate resistance for years prior to that, but the first GR weed population reported in a GR soybean crop in the US was 2001 (Van Gessel, 2001), almost five years prior.

In addition to field-level data on grower production practices, county-level data regarding the number of soybean growers by county were obtained from the 2007 Agricultural Census, which publicly reports the number of soybean growers at the county level. Data on the area of each county was obtained from the U.S. Census Topologically Integrated Geographic Encoding and Referencing GIS-layer.

Estimates of the average temperature and precipitation for the county containing each grower were made using weather-station level data obtained from the National Climate Data Center from its Global Historical Climatology Network (GHCN) Monthly database.\(^9\) Specifically, for every county in the sample, I took an inverse-distance weighted average of monthly temperature and precipitation means for every station within 250 miles of the center of every county. This approach to estimating county-level weather variables is similar to the one used in Mendelsohn et al. (1994). Descriptive statistics for each of these variables used to estimate the models described above are reported in Table 2.1.

\(^9\) The GHCN Monthly database includes monthly averages of weather observations from over 70,000 surface stations across the world dating back to the year 1900.
2.7. Results

The OLS results for the model in Eq.15 are reported in Table 2.2 in column 3. I find that the quadratic term for the neighbor density variable is significant, implying that the observed relationship is nonlinear (a joint hypothesis test conducted using the F test statistic reveals that the coefficients on the neighbor density variables are significantly different from zero at the 5% significance level.).

Specifically, the linear term is negative and the quadratic term is positive. This suggests that the partial effect of neighbor density on a grower’s glyphosate application rate changes as neighbor density increases. Specifically, a higher neighbor density has a negative effect on the glyphosate application rate until the density reaches approximately 2.7 farms per 1,000 acres, after which the effect becomes positive. This could suggest that the benefits associated with having more neighbors discussed earlier, like information spillovers, dominate for low levels of neighbor density. But, as neighbor density gets larger the problems associated with weed mobility become stronger and possibly more difficult to internalize through Coasean bargaining. Note that this result is robust to the other specifications of Eq.15 included in Table 2.2.

Because the quadratic term is significant, this makes testing my central hypothesis more difficult because I must choose specific densities at which to conduct the test. To account for the fact that the partial effect changes as neighbor density increases, I conduct the test at the minimum neighbor density in this sample, the 25th percentile, the 50th percentile, the 75th percentile, and the maximum neighbor density. The results of these tests are reported
in Table 2.3. As one can see, I cannot reject the null hypothesis that the partial effect is equal to zero except when assuming neighbor density is the maximum value. Specifically, if neighbor density is 5.951, an increase in that density of 1 neighbor per 1,000 acres will increase the mean glyphosate application rate by 0.169 pounds per acre. Given that mean glyphosate application rates in this sample were 1.33 pounds per acre, this effect represents a 13% increase in average glyphosate use.

In addition to the relationship between neighbor density and glyphosate application rate, the coefficients on temperature, row width, and no-till are statistically significant and in the direction expected by the our discussion in Section 2.2. Specifically, a 1 degree increase in temperature will decrease glyphosate application rate by 0.006 pounds per acre (consistent with temperature making glyphosate less effective). Similarly, a 1 inch increase in row width will increase glyphosate application rate by 0.004 pounds per acre (consistent with wider row widths allowing more weeds to grow that must be controlled chemically). Lastly, a farmer pursuing no-till growing techniques will apply 0.12 more pounds of glyphosate per acre (consistent with not tilling leading to more weeds that must be controlled chemically). Note that even though temperature and row width have statistically significant impacts on glyphosate, it is not clear that an increase in glyphosate application rates of less than 0.01 pounds is economically significant.

The OLS results for the model in Eq.16 are reported in Table 2.4 in column 3. As expected, the relationship between neighbor density and glyphosate application rates is different for the Appalachian region. Specifically, once the interaction terms are considered,
the linear term becomes positive and the quadratic term becomes negative. As a result, a higher neighbor density has a positive effect on the glyphosate application rate until the density reaches approximately 3.2 farms per 1,000 acres, after which the effect becomes negative. This result is significant at the 5% level and consistent across the other model specifications included in Table 2.4. This could suggest that strategic externalities are more of a problem in this region and growers have a difficult time internalizing them, even at low densities.

2.8. Conclusions

Over all, I do not find evidence that the emergence of glyphosate resistance was the result of a national “tragedy of the commons” problem. Instead, my results suggest that strategic externalities only dominated other external factors in areas that are densely populated by soybean growers. According to the base model, a higher neighbor density actually has a negative effect on the glyphosate application rate until the density reaches 2.7 farms per 1,000 acres, only after which does the effect becomes positive.

To better understand which areas may have a common property resource management problem, we could use data collected from 2007 Agricultural Census. According to data collected from the 2007 Agricultural Census, only 393 counties in the United States have farm densities that exceed 2.7 per 1,000 acres (approximately 11% of all counties). Further analysis reveals that these counties seem to be concentrated in the Appalachian region (Kentucky, North Carolina, Tennessee, Virginia, and West Virginia). Specifically, almost
40% of these 393 counties are located in the Appalachian region. Therefore, one would expect strategic externalities to be more of a problem in this region. This prediction is consistent with the findings of the second model.

The results presented in this paper could be useful for policy makers. Specifically, these results suggest that a national herbicide management policy managed by the U.S. Environmental Production Agency may be unnecessary for internalizing strategic externality problems because they may not be important a driving factor of glyphosate application rates in most areas. Instead, regional and local efforts, particularly in the Appalachian region, might be preferred.
2.9. Figures and Tables

Source: Heap (2013)

Figure 2.1. Confirmed glyphosate-resistant weed populations in North America
Figure 2.2. Herbicide Use Practices on Soybean Acres (1996-2012)
Source: Powles and Duke (2010)

Figure 2.3. Diversity of Herbicide Use by Soybean Growers (1995-2005)
Source: Livingston et al., 2013

Figure 2.4. Influence of Neighbors on Effectiveness of Glyphosate Resistant Management Practices
Figure 2.5. Nash Equilibrium Glyphosate Use
Figure 2.6. USDA Farm Production Regions
Figure 2.7. County Farm Density in U.S. and Appalachian Region
Table 2.1. Descriptive Statistics of Soybean Grower Characteristics (n=2,258)

<table>
<thead>
<tr>
<th>Variable (units)</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neighbor Density (Farms per 1,000 Acre)</td>
<td>1.87</td>
<td>0.88</td>
<td>0.19</td>
<td>5.95</td>
</tr>
<tr>
<td>Total Glyphosate Application (lbs. of a.i. per acre)</td>
<td>1.33</td>
<td>0.56</td>
<td>0.12</td>
<td>3.00</td>
</tr>
<tr>
<td>Soybean Farm Size (Acres)</td>
<td>723.16</td>
<td>840.74</td>
<td>6.00</td>
<td>11,900</td>
</tr>
<tr>
<td>Mean Monthly Temperature, Spring (°C)</td>
<td>18.38</td>
<td>4.03</td>
<td>8.35</td>
<td>28.23</td>
</tr>
<tr>
<td>Total Precipitation, Spring (millimeters)</td>
<td>12.93</td>
<td>3.61</td>
<td>5.12</td>
<td>27.76</td>
</tr>
<tr>
<td>Row Width (inches)</td>
<td>17.68</td>
<td>9.41</td>
<td>6.00</td>
<td>40</td>
</tr>
<tr>
<td>No Till (1=Yes)</td>
<td>0.75</td>
<td>0.43</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Crop Rotation (1=Yes)</td>
<td>0.81</td>
<td>.39</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Table 2.2. OLS Estimates for Determinants of Glyphosate Application Rates (Model 1)

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std.</td>
<td>Mean</td>
</tr>
<tr>
<td>Dependent Variable: Glyphosate Application Rate (lbs. per acre)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>-0.139** 0.054</td>
<td>-0.132** 0.059</td>
<td>-0.142** 0.055</td>
</tr>
<tr>
<td>N²</td>
<td>0.026** 0.011</td>
<td>0.024** 0.012</td>
<td>0.026** 0.012</td>
</tr>
<tr>
<td>Size</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>T</td>
<td>-0.006* 0.003</td>
<td>-0.006* 0.003</td>
<td></td>
</tr>
<tr>
<td>P</td>
<td>-0.003 0.004</td>
<td>-0.004 0.004</td>
<td></td>
</tr>
<tr>
<td>Row_Width</td>
<td></td>
<td></td>
<td>0.004*** 0.001</td>
</tr>
<tr>
<td>No_Till</td>
<td></td>
<td></td>
<td>0.121*** 0.027</td>
</tr>
<tr>
<td>Crop_Rot</td>
<td></td>
<td></td>
<td>-0.040 0.036</td>
</tr>
<tr>
<td>Regional Dummies</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>2,258</td>
<td>2,258</td>
<td>2,258</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.036</td>
<td>0.038</td>
<td>0.045</td>
</tr>
</tbody>
</table>

Note: *** denotes p-value < 0.01, ** denotes p-value < 0.05, *p-value < 0.10.
Table 2.3. Testing Partial Effect of Neighbor Density on Glyphosate Application Rate

<table>
<thead>
<tr>
<th>Neighbor Density</th>
<th>$\beta_1 + 2\beta_2 \mathcal{N}_i$</th>
<th>Standard Error</th>
<th>T-Stat</th>
<th>One-Sided 5% Critical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum (0.191)</td>
<td>-0.132</td>
<td>0.052</td>
<td>-2.55</td>
<td>1.645</td>
</tr>
<tr>
<td>Lower Quartile (1.210)</td>
<td>-0.078</td>
<td>0.030</td>
<td>-2.60</td>
<td>1.645</td>
</tr>
<tr>
<td>Median (1.859)</td>
<td>-0.044</td>
<td>0.019</td>
<td>-2.25</td>
<td>1.645</td>
</tr>
<tr>
<td>Upper Quartile (2.425)</td>
<td>-0.015</td>
<td>0.018</td>
<td>-0.85</td>
<td>1.645</td>
</tr>
<tr>
<td>Maximum (5.951)</td>
<td>0.169</td>
<td>0.088</td>
<td>1.91</td>
<td>1.645</td>
</tr>
</tbody>
</table>

Note: Standard errors were computed for each partial effect by centering and re-estimating the model for each density.
Table 2.4. OLS Estimates for Determinants of Glyphosate Application Rates (Model 2)

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>-0.229***</td>
<td>0.069</td>
<td>-0.216***</td>
</tr>
<tr>
<td>N²</td>
<td>0.043***</td>
<td>0.013</td>
<td>0.039**</td>
</tr>
<tr>
<td>NxApp</td>
<td>0.294**</td>
<td>0.119</td>
<td>0.262**</td>
</tr>
<tr>
<td>N²xApp</td>
<td>-0.052**</td>
<td>0.024</td>
<td>-0.046*</td>
</tr>
<tr>
<td>Size</td>
<td>&lt;0.001**</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>T</td>
<td>-0.005</td>
<td>0.003</td>
<td>-0.005</td>
</tr>
<tr>
<td>P</td>
<td>-0.002</td>
<td>0.004</td>
<td>-0.002</td>
</tr>
<tr>
<td>Row_Width</td>
<td></td>
<td></td>
<td>0.004***</td>
</tr>
<tr>
<td>No_Till</td>
<td></td>
<td></td>
<td>0.121***</td>
</tr>
<tr>
<td>Crop_Rot</td>
<td></td>
<td></td>
<td>-0.038</td>
</tr>
<tr>
<td>Regional Dummies</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>2,258</td>
<td>2,258</td>
<td>2,258</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.039</td>
<td>0.041</td>
<td>0.052</td>
</tr>
</tbody>
</table>

Dependent Variable: Glyphosate Application Rate (lbs. per acre)

Note: *** denotes p-value < 0.01, ** denotes p-value < 0.05, *p-value < 0.10.
2.10 References


CHAPTER 3

How Do Growers Respond to Declines in Herbicide Susceptibility? Evidence from U.S. Cotton and Soybean Growers

3.1. Introduction

Glyphosate-resistant (GR) varieties of crops such as soybeans and cotton have been widely adopted around the world because they are genetically modified to be resistant to glyphosate (marketed by Monsanto as “Roundup”), a broad spectrum herbicide associated with low environmental impact. According to recent studies, GR crops represent more than 80% of the 120 million hectares of transgenic crops grown annually worldwide (Duke and Powles, 2009). However, the economic viability of GR crop technology is being diminished as glyphosate is becoming less effective in many areas due to the spread of weeds that are also resistant to glyphosate.

Glyphosate-resistant weeds are members of a weed population that have the inherited ability to survive a glyphosate application that would normally be lethal to the wild variety of the plant (Zimbdal, 1999). Weeds with the ability to survive standard glyphosate applications have been spreading rapidly in recent years because the increased use of glyphosate associated with the adoption of GR crops has given them a reproductive advantage. The first verified GR weed in the United States (US) was identified in a GR soybean crop in Delaware in 2001 (Van Gessel, 2001). Since that time, GR weeds have been identified in many other crops and in many other states. Data collected by Heap (2012) reveal that GR weed species
have already been confirmed in 29 states across the U.S. The spread of glyphosate resistance over the past 10 years is illustrated in figure 3.1.

Growers are understandably concerned by the spread of this trend. As GR weeds become a larger fraction of the weed populations that growers face, glyphosate will become increasingly less effective at fighting these pests. As a result, growers will either have to apply more glyphosate to eliminate the same number of weeds as before or they will have to use substitute methods of weed control. The choice that growers make could have significant future consequences. For example, if most growers choose to use more glyphosate, then this could exacerbate the problem of GR weeds in the future.

Determining how growers have responded to recent declines in the susceptibility of weed populations to glyphosate is a difficult task. One recent study that tried to answer that question was Sosnoskie and Culpepper (2014), which measured how the herbicide use of cotton growers in Georgia changed after the appearance of GR amaranthus palmeri (pigweed) in 2006. The primary data source for this study was a survey of 65 cotton growers in Georgia that was fielded in 2010 and 2011. The survey asked respondents to recall how much glyphosate and other herbicides they used between 2000 to 2005 and 2006 to 2010. The authors found that, on average, the cotton growers they surveyed used less glyphosate per treated acre in the 2006 to 2010 period than they did during the 2000 to 2005 period (magnitude not reported). Similarly, the fraction of planted acres treated with glyphosate post-planting fell from over 90% during the 2000 to 2005 period to 75% during the 2006 to 2010 period. Sosnoskie and Culpepper attribute the decline in glyphosate use to growers
moving to other herbicides as the spread of GR pigweed made glyphosate less effective. However, they do not outline a model of cotton grower behavior to justify this assertion.

Sosnoskie and Culpepper’s findings are interesting and make an important contribution to understanding how grower are responding to the spread of GR weeds. However, the analytical approach employed by Sosnoskie and Culpepper is problematic for two fundamental reasons. First, Sosnoskie and Culpepper control for the level of weed susceptibility to glyphosate by comparing herbicide use before and after 2006, the year GR weeds were first verified. The assumption here is that weed populations after 2006 will tend to be less susceptible to glyphosate than previous weed populations. Although this is likely true, it is important to note that this observation does not allow us to discern how much less susceptible weed populations were during this period. In addition, it also ignores the possibility that GR weeds were present on Georgia cotton farms prior to 2006, but not verified by an academic source. This is not to say that Sosnoskie and Culpepper’s approach was wrong. Instead, the point to stress here is that the susceptibility of a weed population to a particular herbicide is fundamentally unobservable.

Second, by only comparing the unconditional means between time periods, Sosnoskie and Culpepper end up attributing all the differences between pre- and post-2006 glyphosate application rates to the emergence of GR weeds. This is important because there were significant changes during this period in factors that may also influence herbicide use such as prices and technology. For example, between 2000 and 2005, the real price of glyphosate fell by 31% as a result of Monsanto losing its patent on the pesticide. However, between
2006 and 2009, the price rose by 37% due increased international demand and supply disruptions among Chinese glyphosate manufacturers (Western Farm Press, 2008). Conventional microeconomic theory would suggest that, other things being equal, cotton growers would have used more glyphosate in the 2000 to 2005 period than the 2006 to 2009 period because the price was lower. So one must ask how much of the pattern in glyphosate use that Sosnoskie and Culpepper observe are explained by these price movements.

In order to accurately determine how growers have responded to declines in the susceptibility of weed populations to glyphosate, one would want to 1) use a continuous measure of how susceptible weed populations are to glyphosate, and 2) control for potential confounding variables. Currently, no study has attempted to do this. The goal of this paper is to fill this gap in the literature. To achieve this goal, I create two unbalanced panel datasets, one for cotton growers and one for soybean growers, using state-level data on glyphosate application rates collected by the U.S. Department of Agriculture (USDA) as part of its Agricultural Resource Management Survey (ARMS). I focus on cotton and soybean growers because they have likely been the most affected by the emergence and spread of GR weeds. This is because they have the widest adoption of GR crop technology of any commodity for which ARMS collects data (Fernandez-Cornejo et al., 2014).

Using these data, I develop a panel model to test whether growers respond to declines in the herbicide effectiveness by increasing or decreasing their use of the herbicide. This model overcomes the fact that the susceptibility of weed populations is unobservable by modeling susceptibility as a depletable stock whose equation of motion can be
parameterized. This equation of motion captures the intuition that the change in a weed populations “stock” of glyphosate susceptibility from one period to the next depends on how much glyphosate is applied by growers. If growers apply more glyphosate this period, this will deplete the “susceptibility stock” available for use next period by giving GR weeds more of a reproductive advantage this period so that they represent a larger fraction of the weed population next period.

Results of my analysis indicate that growers respond to declines in the susceptibility stock by using less glyphosate. For cotton growers, I find that a 1-pound increase in the mean glyphosate application rate in period t-1 is associated with a mean decrease in the glyphosate application rate of 0.46 pounds per acre (p<0.05), holding everything else equal. Similarly, for soybean growers, I find that a 1-pound increase in the mean glyphosate application rate in period t-1 is associated with a mean decrease in the glyphosate application rate of 0.38 pounds per acre (p<0.05), holding everything else equal.

The remainder of the paper is organized as follows. In the next section, I explore the economic theory surrounding weed management behavior. Third I describe my data and empirical approach to estimating the partial effect of changes in the susceptibility stock on glyphosate application rates. After reporting the results of the panel model estimation, I conclude with a discussion of the implications of these results for policy makers.
3.2. Economic Models of Weed Management Behavior

This section develops two models of weed management behavior to better understand the conditions that determine whether a grower will respond to declines in herbicide productivity by using more herbicide or by using less. In both models, I incorporate changes in herbicide productivity by following economic convention and assuming that the susceptibility of a weed population to a particular herbicide can be conceived as a finite resource that growers deplete through continual use (see Hueth and Regev, 1974 or Clark and Carlson, 1990).

In the first model, I consider the herbicide application decision of a profit-maximizing grower that perceives the stock of herbicide susceptibility to be exogenous. Under this assumption, the grower does not consider how his herbicide application this period will influence the level of susceptibility stock next period. As a result, his herbicide application decision is solely focused on maximizing current period profits. This model best describes a situation where the stock of herbicide susceptibility is considered a common property resource.  

The second model I consider involves a forward-looking grower that recognizes his herbicide use has an impact on future herbicide productivity (i.e. the future level of the susceptibility stock). In this scenario, a firm is not responding to exogenous declines in herbicide productivity. Instead, herbicide productivity is endogenous and growers are

---

10 For more details on why this is the case, see Clark and Carlson (1990).
scheduling its decline to maximize lifetime profits. This model best describes a situation where the stock of herbicide susceptibility is considered a private property resource.\textsuperscript{11}

After discussing both models, I end this section with a summary of their main predictions. Specifically, I outline the conditions that will lead a grower respond to declines in herbicide susceptibility by increasing herbicide use decreasing herbicide use. Although the results of these models will not be used directly in the empirical strategy, they will help interpret the results.

Note that the modeling approach I take in this section assumes the amount of herbicide applied and the level of susceptibility stock are inputs that enter directly into a production function. This approach is most similar to the one used by Carlson (1977) and Clark and Carlson (1990). However, an alternative modeling approach proposed by Lichtenberg and Zilberman (1985) is to assume that the amount of herbicide applied and the level of susceptibility stock are inputs that enter the production function indirectly through a damage abatement function. The main difference between these two modeling approaches is that the Lichtenberg and Zilberman approach implies the amount of herbicide applied and the level of susceptibility stock are always substitutes in the production process. By contrast, the Carlson approach does not place a theoretical restriction on whether the two inputs could be substitutes or complements (although it can be argued you would expect the inputs to be complements if the production function exhibits constant returns to scale). In the next section it will become clear that growers will act differently if these inputs are substitutes than if they

\textsuperscript{11} Ibid.
are complements. Therefore, I chose to use the Carlson approach so that I could discuss these differences. However, a full treatment of the Lichtenberg and Zilberman approach is provided in Appendix 1.

3.2.1 Exogenous Herbicide Susceptibility

Consider a farm facing a competitive market whose production process is characterized by the following production function:

$$Y_t = f(G_t, S_t, X_t)$$

where $Y_t$ is amount of output produced at time $t$, $G_t$ is the amount of herbicides applied at time $t$, $S_t$ is the level of herbicide susceptibility stock at time $t$, and $X_t$ is an aggregate of other inputs. Each are assumed to be normal inputs in a production process that exhibits constant returns to scale ($\frac{\partial f}{\partial G_t} > 0$, $\frac{\partial f}{\partial S_t} > 0$, $\frac{\partial f}{\partial X_t} > 0$, and $f(\alpha G_t, \alpha S_t, \alpha X_t) = \alpha Y_t$ where $\alpha > 0$).

The farm owner solves the profit maximization problem:

$$\max_{\{G_t\}} \pi_t = Pf(G_t, S_t, \bar{X}) - wG_t - q\bar{X}$$

where $P$ is the market price of the farm’s output, $w$ is the market price of herbicides, and $q$ is the market price of the aggregate input. The herbicide susceptibility stock has no price as it is assumed to be an exogenous feature of the environment. Because I am primarily concerned with the impact of changes in $S_t$ on $G_t$, I assume that all other inputs are fixed at $\bar{X}$ for analytical simplicity.

The first and second-order conditions for the profit-maximization problem are:
FOC: \[
\frac{\partial \pi}{\partial G_t} = P \frac{\partial f}{\partial G_t} - w = 0
\] (3)

SOC: \[
\frac{\partial^2 \pi}{\partial G_t^2} = P \frac{\partial^2 f}{\partial G_t^2} < 0
\] (4)

The first order condition implies that herbicide will be applied until the value of marginal product of herbicide \((P \times MP_G)\) or \(VMP_{G,t}\) equals its market price \((w_{t,g})\). The second order condition implies that the marginal product must be decreasing in glyphosate. Figure 3.2 illustrates the optimal herbicide application rate.

How the optimal herbicide application rate will respond to an exogenous change in the susceptibility stock will depend on whether \(S_t\) and \(G_t\) are substitutes or complements in production. If the two inputs are complements \(\left(\frac{\partial MP_G}{\partial S_t} > 0\right)\), then a decrease in \(S_t\) would lower \(MP_G\) and reduce the optimal herbicide application rate. If the two inputs are substitutes \(\left(\frac{\partial MP_G}{\partial S_t} < 0\right)\), then a decrease in \(S_t\) would raise \(MP_G\) and increase the optimal herbicide application rate.

One cannot say \textit{a priori} whether \(S_t\) and \(G_t\) are substitutes or complements. However, given the reasonable assumption that the production process exhibits constant returns to scale, one can say that inputs tend to be complements on average. As a result, without any other information, I would expect a decrease in \(S_t\) would lower \(MP_G\). But whether this is true or not is an empirical matter. As previously stated, this prediction contrasts sharply with the Lichtenberg and Zilberman approach, which requires \(S_t\) and \(G_t\) to be substitutes.

Lichtenberg and Zilberman’s prediction is derived in detail in the appendix.

---

12 This proposition can be proven using Euler’s Theorem. See Becker (2007).
3.2.2 Endogenous Herbicide Susceptibility (Forward-looking Grower)

As previously discussed, the susceptibility stock this period is negatively related to herbicide use in previous periods. This relationship can be stated generally as follows:

\[ S_t - S_{t-1} = f(G_{t-1}) \]

Following Clark and Carlson (1990), let the difference equation defining depletion of the susceptibility stock be represented by the first-order Taylor approximation:

\[ S_t - S_{t-1} \approx \varphi - \delta G_{t-1} \] (5)

where \( \varphi \) can be interpreted as an exogenous rate of change in the susceptibility stock and \( \delta \) is a constant rate of depletion for each unit of herbicide use.

If a grower is forward-looking and recognizes that his herbicide application decision influences his future productivity, it is reasonable to assume that he will seek to choose the herbicide application rate that maximizes profits over his lifetime and not just a single period. Therefore, a forward-looking, infinitely-lived farm owner solves the profit maximization problem:

Maximize over \( \{G_t\} \)

\[ \pi_t = \sum_{t=0}^{T} \left( \frac{1}{1+r} \right)^t \left[ P_f(G_{t+i}, S_{t+i}, \bar{X}) - wG_{t+i} - q\bar{X} \right] \]

Subject to

\[ S_t - S_{t-1} = \varphi - \delta G_{t-1} \] (6)

where \( r \) is the discount rate.

The Lagrangian expression for this constrained maximization problem takes the form:

\[ L = \sum_{i=0}^{\infty} \left( \frac{1}{1+r} \right)^i \left[ P_f(G_{t+i}, S_{t+i}, \bar{X}) - wG_{t+i} - q\bar{X} - \lambda_{t+i}(S_{t+1+i} - S_{t+i} + \delta G_{t+i} - \varphi) \right] \]

(7)
Differentiating the Lagrangian with respect to each variable gives the first order conditions:

\[
\frac{\partial \mathcal{L}}{\partial G_t} = P \frac{\partial f}{\partial G_t} - w - \delta \lambda_t = 0 \tag{8}
\]

\[
\frac{\partial \mathcal{L}}{\partial S_{t+1}} = -\lambda_t + \frac{1}{1+r} \left( P \frac{\partial f}{\partial S_{t+1}} + \lambda_{t+1} \right) = 0 \tag{9}
\]

\[
\frac{\partial \mathcal{L}}{\partial \lambda_t} = S_{t+1} - S_t + G_t - \varphi = 0 \tag{10}
\]

\[
\lim_{T \to \infty} \left( \frac{1}{1+r} \right)^T \lambda_T S_T = 0 \quad \text{Transversality Condition} \tag{11}
\]

\[
S_0 > 0 \quad \text{Given Stock} \tag{12}
\]

Equations 8 and 9 can be combined to obtain a modified version of the profit-maximization condition contained in equation 3:

\[
P \frac{\partial f}{\partial G_t} = w + \frac{1}{1+r} \left( P \frac{\partial f}{\partial S_{t+1}} + \frac{1}{\delta} \left( P \frac{\partial f}{\partial G_{t+1}} - w \right) \right) \tag{13}
\]

As before, this condition implies that a farm owner will apply herbicide until the value of marginal product in period t \((P \times MP_{G_t} \text{ or VMP}_{g,t})\) equals its marginal cost. But the marginal cost is now composed of three components. The first component is the price of purchasing a unit of herbicide in period t. This component of marginal cost is captured, as before, by w.

The second component is the present value of the additional loss in herbicide productivity in period t+1 from using a unit of herbicide in period t. If a grower uses a unit of herbicide in period t, then the marginal productivity of the herbicide will decrease in period
t+1 as the susceptibility stock is depleted. This component of marginal cost is captured
by \( \frac{1}{1+r} \left( P \frac{\partial f}{\partial S_{t+1}} \right) \). This can be referred to as the “stock effect”.

The third component of marginal cost is the present value of the marginal opportunity
cost of using a unit of herbicide in period t instead of period t+1. Specifically, if the farm
owner had not used that last gallon of glyphosate in period t, then his marginal productivity
in period t+1 would not have decreased by the amount captured in the second component of
marginal cost \( \left( \frac{1}{1+r} \left( P \frac{\partial f}{\partial S_{t+1}} \right) \right) \). In other words, the farm owner gave up the opportunity to use
a more productive unit of herbicide in period t+1 by using it in period t. This marginal
opportunity cost is captured by \( \frac{1}{1+r} \frac{1}{\delta} \left( P \frac{\partial f}{\partial G_{t+1}} - w \right) \). I refer to the sum of the stock effect and
the marginal opportunity cost as the marginal user cost (MUC\(_{g,t}\)).

If one assumes that \( S_t \) and \( G_t \), are complements, it can be shown that the herbicide
application rate will fall as \( S_t \) is depleted. Intuitively, this can be seen from figure 3.3. As the
stock declines from period t to period t+1, VMP\(_{g,t+1}\) will shift to the right because that \( S_t \) and
\( G_t \). Similarly, MUC\(_{g,t+1}\) will also shift to the right because the opportunity cost component of
marginal \( \frac{\partial f}{\partial S_{t+1}} \) will grow larger as the stock gets smaller due to diminishing marginal
returns. As a result, the shifts in the MVP\(_{g,t+1}\) and MUC\(_{g,t+1}\) curves will both work to reduce
herbicide use. These shifts are illustrated in figure 3.4. Note that due to additional the shift in
the MUC\(_{g,t+1}\) curve, the forward-looking grower will reduce his herbicide use by even more
than the myopic grower portrayed in the previous section, since that grower would only be
responding to changes in MVP\(_{g,t+1}\).
The fact that growers will reduce herbicide application as $S_t$ declines (assuming $S_t$ and $G_t$, are complements) can also be shown more formally by rearranging (13) as follows:

$$\frac{(P\frac{\partial f}{\partial G_{t+1}}-w)(P\frac{\partial f}{\partial G_t}-w)}{(P\frac{\partial f}{\partial G_{t+1}}-w)} = r - \frac{(P\frac{\partial f}{\partial S_{t+1}})}{(P\frac{\partial f}{\partial G_t}-w)}$$  (14)

Equation 14 says that along the optimal path the net marginal value of the susceptibility stock $(P\frac{\partial f}{\partial G_t} - w)$ is increasing at a rate of $(r - \frac{(P\frac{\partial f}{\partial S_{t+1}})}{(P\frac{\partial f}{\partial G_t}-w)})$. If $S_t$ and $G_t$ are complements, then the only way that the net marginal value could rise over time as the susceptibility stock falls is if less herbicide is used in each subsequent period.

Note that the relationship in (14) is similar to the one that underlies the Hotelling Rule. Specifically, the Hotelling Rule rests on the relationship that a resource owner will only be indifferent at the margin between leaving a resource “in the ground” or selling it when the net marginal value from extracting the resource rises at the discount rate (i.e. the interest rate). If the net marginal value is rising faster than the interest rate, then the resource is earning a higher return “underground” than money “above ground” and the owner will prefer to not extract the resource.

By contrast, in this model, the net marginal value from depleting the susceptibility stock $(P\frac{\partial f}{\partial G_t} - w)$ does not have to rise as fast as the interest rate to keep the resource owner indifferent at the margin between exploiting susceptibility now or later. This makes intuitive sense because the farmer using an extra pound of herbicide today is penalized in two ways. First, by extracting a unit of the susceptibility stock today, he gives up the opportunity of
extracting that unit tomorrow. Second, extracting a unit of the susceptibility stock today also implies that the stock of susceptibility will be lower tomorrow, which means the herbicide will be less effective. This “stock effect” (captured by \( \left( \frac{p \frac{\partial f}{\partial S_t}}{p \frac{\partial f}{\partial G_t} - w} \right) \)) gives the grower an extra reason to use less herbicide today that Hotelling’s resource owner did not have.

Note that until this point I have only considered cases where \( S_t \) and \( G_t \) are complements. But what happens if these two inputs are substitutes? If this is the case, then there is no clear prediction for how forward-looking growers will react as the susceptibility stock is depleted without more information about the production function. This fact can be illustrated using figure 3.3. If \( S_t \) and \( G_t \) are substitutes, then the marginal product of \( G_t \) will increase as declines (VMP\(_g\) will shift to the right). By contrast, the opportunity of using an additional unit of herbicide today will still rise because (MUC\(_g\) will shift to the left). In other words, when \( S_t \) and \( G_t \) are substitutes, then the VMP\(_g\) curve and MUC\(_g\) shift in opposing directions. As a result, whether growers respond to a declining susceptibility stock will on whether the shift in the VMP\(_g\) curve or the shift in the MUC\(_g\) curve dominates.

### 3.2.3 Summary of Predictions for Weed Management Behavior

The models above illustrate the conditions that will lead growers to either increase or decrease their herbicide use in response to declines in the susceptibility stock. Specifically, I find that if \( S_t \) and \( G_t \) are complements, growers will reduce their use of an herbicide as it becomes less productive, regardless of whether growers view susceptibility as an exogenous feature of the environment or a product of their own decisions over time.
By contrast, if $S_t$ and $G_t$ are substitutes, how growers respond will differ based on whether they view susceptibility as exogenous or a product of their own decisions over time. Specifically, if growers view susceptibility as an exogenous feature of their environment, they will always respond by using more herbicide. However, if growers believe that susceptibility is influenced by their decisions, then we cannot predict how they will respond to declines in susceptibility without more information about the production technology they are using.

3.3. Empirical Strategy

I estimate the partial effect of decreases in susceptibility stock on glyphosate application rates by estimating glyphosate demands for U.S. cotton and soybean growers using an unbalanced panel of state-level herbicide application data published by the National Agricultural Statistics Service (NASS). Specifically, I develop a panel model that addresses the problem of measuring the susceptibility stock and eliminates unobserved, time invariant state-level heterogeneity through first differences.

The baseline demand model that I seek to estimate takes the form:

$$G_{it} = \gamma_0 + \gamma_1 S_t + \gamma_2 w_t + \gamma_3 P_{it} + \gamma_4 q_t + \gamma_5 t + z_i' \alpha + v_{it}$$  \hspace{1cm} (15)

where for state $i$ and year $t$, $G_{it}$ is the mean glyphosate application rate, $S_t$ is the susceptibility stock of the weed population, $w_t$ is the market price of glyphosate, $P_{it}$ is the price of the output, $q_t$ is the price of other inputs, $t$ is a time trend included to capture
technological change, \( z_t \) is an \( M \)-dimensional row vector of time-invariant explanatory variables, \( \alpha \) is an \( M \)-dimensional column vector of parameters, and \( v_{it} \) is a random error term.

If (15) could be estimated, the hypothesis of how growers adjust their glyphosate use in response to changes in the susceptibility stock could be stated as a test on a single parameter. Specifically, if growers decrease glyphosate use in response to declines in the susceptibility level, the coefficient \( \gamma_1 \) would be positive. Conversely, if growers decrease glyphosate use in response to declines in the susceptibility level, the coefficient \( \gamma_1 \) would be positive.

The obvious problem estimating (15) is that the stock of susceptibility cannot be observed. One way of addressing this problem is to use a proxy. This was the approach Carlson (1977) pursued in his study on the long-term productivity of insecticides. Specifically, he constructed a pesticide resistance index using data on species of insects that had been identified as resistant to particular insecticides.

Although this approach can be quite useful, it suffers from two limitations. First, using proxies can make problems associated with measurement error more likely, which could result in inconsistent parameter estimates. Second, using measures based on observed pesticide resistance as a proxy for susceptibility stock depletion assumes that the stock is not being depleted unless there are resistant pests. This seems like a limited measure since one could argue that it was the depletion of the susceptibility stock that led to the emergence of the resistant pest.
This point can be made more clearly using the intertemporal profit maximization model discussed in Section 2.1.2. Specifically, this model showed that declines in $S_{it}$ affect the profit-maximizing level of glyphosate applications in two ways. First, if $S_{it}$ and $G_{it}$ are complements, then reductions in $S_{it}$ can affect the marginal productivity of glyphosate by making it a less effective herbicide. This effect is what is associated with the spread of GR weeds. However, the second effect is that as $S_{it}$ decreases, the opportunity cost of using glyphosate increases for two reasons: 1) each pound of glyphosate a grower uses today is one he cannot use tomorrow and 2) each pound of glyphosate a grower uses today is associated with a reduction in the marginal productivity of glyphosate at some point in the future. As a result, even if there are no GR weeds present today, a forward looking grower will take account of the future opportunity cost of depleting the susceptibility stock.

Since the susceptibility stock cannot be observed and it is difficult to construct an appropriate proxy, I propose that an alternative approach would be to eliminate $S_{it}$ from the model entirely. This can be accomplished by remembering that the susceptibility stock this period is negatively related to glyphosate use in previous periods. Following Clark and Carlson (1990), I assume that the depletion of the susceptibility stock from one period to another can be described by the following first-order Taylor approximation:

$$S_{it} - S_{it-1} = \varphi - \delta G_{it-1}$$

(26)

where $\varphi$ can be interpreted as an exogenous rate of change in the susceptibility stock and $\delta$ is a constant rate of depletion for each unit of herbicide use.
Sustainability stock can now be eliminated from the model by taking the first difference of (15) and using (16) to substitute for the change susceptibility stock. This yields the following first-difference model:

\[ \Delta G_{it} = \theta_0 + \theta_1 G_{it-1} + \theta_1 \Delta w_t + \theta_2 \Delta P_{it} + \theta_3 \Delta q_t + \epsilon_{it} \]  

(17)

where \( \theta_0 \) is the sum of \( \gamma_5 \) and the product of product of \( \gamma_1 \) and \( \varphi \), \( \theta_1 \) is the product of \( \gamma_1 \) and \( \delta \), and \( \epsilon_{it} \) is \((v_t - v_{t-1})\).

Although this transformation addresses the problem of not being able to observe \( S_t \), it creates several new problems. First, the parameter of interest, \( \gamma_1 \) can no longer be identified. As a result, the magnitude of changes in \( S_t \) on \( G_t \) cannot be estimated. However, the hypothesis test described above can still be performed because the sign of \( \delta \) is known to be negative from the scientific literature discussed above.\(^\text{13}\) Thus, if \( \theta_1 \) is negative, then \( \gamma_1 \) is positive and growers respond to declines in the susceptibility stock by decreasing their glyphosate use. Similarly, if \( \theta_1 \) is positive, then \( \gamma_1 \) is negative and growers respond to declines in the susceptibility stock by increasing their glyphosate use. This test can be performed with a two-sided t-test.

The second problem in estimating (17) is that it includes a lagged dependent variable, which makes obtaining consistent estimates of the model parameters difficult. This is because the lagged dependent variable and the error term \( \epsilon_{it} \) are both functions of the previous period’s residual \((v_{t-1})\). As a result, the two are necessarily correlated and Ordinary Least Squares (OLS) estimates of (17) will be biased and inconsistent (Nickell, 1981). To

\(^{13}\) Applying more glyphosate this year increases selection pressure by providing GR weeds with a reproductive advantage that lowers the level of glyphosate susceptibility next period by increasing the fraction of GR weeds that must be controlled.
overcome this problem, I estimate (17) using a two-stage least squares (TSLS) estimator with cluster-robust standard errors using the two-period lagged value of the dependent variable as instrument.

I chose this variable as the instrument because it satisfies the two conditions that must be met for an instrument to be valid. The first condition is that the instrument must be correlated with the endogenous variable. This is almost certainly the case as the amount of glyphosate used in previous periods will influence current through their impact on the susceptibility stock. The second condition a valid instrument must satisfy is that it must be uncorrelated with the error term in the explanatory equation. This assumption is most likely to be violated in this circumstance if serial correlation is present (Angrist and Pischke, 2008). If the model is correctly specified, this should not be a problem. However, a Durbin-Watson test can be performed on the residuals to determine if serial correlation is present.

In order to explore how coefficient estimates change in response to different model specifications, I also examine a semi-log version of (17). Specifically, I estimate the following:

\[
\Delta \ln(G_t) = \theta_0 + \theta_1 G_{t-1} + \theta_1 \Delta \ln(w_t) + \theta_2 \Delta \ln(P_t) + \theta_3 \Delta \ln(q_t) + u_{it} \tag{18}
\]

A final issue with this empirical approach to note is that since I am pursuing a single-equation approach, it is possible for simultaneity issues to arise between the glyphosate application rate and the price of glyphosate. However, there are two reasons to suspect that the market price can be treated as exogenous here. First, the global adoption of GR crop varieties has led to glyphosate being traded worldwide. As a result, the influence of demand
by U.S. growers has on global prices has been diminishing. Second, the supply of glyphosate has varied far more over the time period in question than demand for glyphosate. This can be illustrated by the fact that glyphosate prices have fallen significantly since the late 1990s, despite the increasing use of glyphosate (see figure 3.5 and 3.6). This persistent decline in glyphosate prices has likely been driven by the entry of firms producing generic glyphosate after Monsanto’s patent on glyphosate expired in 2000. The assumption that glyphosate prices are exogenous could be tested using a Wu-Hausman test if a suitable instrument for price was identified. However, at the time of this writing, I have not identified such an instrument.

3.4. Data

The primary data source for this study on state-level glyphosate application rates is the annual ARMS cross-sectional survey. This survey has been conducted since 1996. However, the survey does not cover growers of every commodity every year. Specifically, state-level data for cotton growers are only reported for 1996, 1997, 1998, 1999, 2000, 2001, 2003, 2007, and 2010. Similarly, state-level data for soybean growers are only reported for 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2006, and 2012. The gaps in data collection after 2002 for both commodities have serious consequences for my analysis. This is because my empirical approach requires a state to have at least three years of continuous data to estimate (17) and (18) using TSLS. As a result, only data for the years 1996 to 2001 will be included for cotton growers and only data for the years 1996 to 2002 will be included for soybean.
growers. Figures 7 and 8 illustrate which states are included in the dataset for cotton growers and the dataset for soybean growers.

In addition to data on state-level glyphosate application rates, data were also collected on input and output prices. Specifically, data on the mean price farmers paid for glyphosate across the U.S. between 1990 and 2002 were obtained from Agricultural Chemical Usage Report. Data on mean prices for cotton and soybeans received by farmers were obtained for each state and each year between 1990 and 2002 from the USDA’s annual commodity cost and returns report. Descriptive statistics for each of these variables are reported in table 3.1.

3.5. Results

In this section, I present and discuss parameter estimates for the two models developed in Section 3.3. However, before presenting and discussing the estimation results, it is instructive to start by looking at some nonparametric evidence to check whether glyphosate application rates appear correlated at all with the depletion of the susceptibility stock. Therefore, figures 3.9 and 3.10 plot the difference in glyphosate application rates against lagged glyphosate application rates for both corn and soybean growers. As one can see, the relationship is negative for both crops.
3.5.1 Cotton Growers

First I discuss testing instrument strength. The first-stage results for model 1 and model 2 are reported in table 3.2 (column 3) and in table 3.3 (column 3) respectively. As one can see, for both models, the instrument is statistically significant at less than the 1 percent level. In fact, the F-statistic on the excluded instrumental variable exceeds the threshold of 10 set by Stock and Yogo (2002) for an IV not to be considered weak. Therefore, I take this as evidence that weak instrument bias is not a major problem for my coefficient estimates.

In addition, it is interesting to note that the coefficient estimate on the instrument (the two-period lagged glyphosate application rate) is positive for both models. This suggests that high levels of glyphosate two periods in the past is associated with a higher level of glyphosate one period in the past. This is the opposite of what I would expect given the discussion above. However, it is important not to try and over interpret this result as it does not take account for differences in price or other variables between the two periods.

Next I discuss testing the partial effect of susceptibility stock on glyphosate application rates in cotton. Parameter estimates for model 1 and model 2 for cotton growers are provided in tables 3 and 4. For comparison I estimated both models using OLS and TSLS. As one can see, the OLS estimates typically share the same sign and significance as the TSLS estimates. However, as discussed as in Section 3, these results are likely inconsistent and should be interpreted with caution. In addition to obtaining parameter estimates, I also inspected the residuals of the TSLS models visually and using the Durbin
Watson test. Neither provided evidence of serial correlation. Therefore, as discussed in Section 3, the TSLS parameter estimates should be consistent.

The TSLS results for estimating model 1 for cotton growers are reported in table 3.4 in column 5. I find that higher glyphosate application rates for cotton growers in previous periods are associated with decreases in glyphosate application rates over subsequent periods. Specifically, I find that a 1-pound increase in the mean glyphosate application rate in period t-1 is associated with a mean decrease in the glyphosate application rate of 0.46 pounds per acre ($p<0.05$), holding everything else equal.

Similarly, the TSLS results for model 2 for cotton growers are reported in table 3.5 in column 5. Again, I find that higher glyphosate application rates for cotton growers in previous periods are associated with decreases in glyphosate application rates over subsequent periods. Specifically, I find that a 1-pound increase in the mean glyphosate application rate in period t-1 is associated with a decrease in the mean glyphosate application rate of 59 percent ($p<0.01$) between period t-1 and t, holding everything else equal. Together, the sign and statistical significance of results from model 1 and model 2 suggest that cotton growers respond to decreases in the susceptibility stock by lowering their glyphosate application rates.

3.5.2 Soybean Growers

As before, I first discuss the results of testing instrument strength. The first-stage results for model 1 and model 2 are reported in table 3.2 (column 5) and in table 3.3 (column
5) respectively. As one can see, for both models, the instrument is statistically significant at less than the 1 percent level. In fact, the F-statistic on the excluded instrumental variable exceeds the threshold of 10 set by Stock and Yogo (2002) for an IV not to be considered weak. Therefore, I take this as evidence that weak instrument bias is not a major problem for my coefficient estimates.

Next I discuss testing the partial effect of susceptibility stock on glyphosate application rates in soybeans. Parameter estimates for model 1 and model 2 for soybean growers are provided in tables 6 and 7. For comparison I estimated both models using OLS and TSLS. As with cotton growers, the OLS estimates typically share the same sign and significance as the TSLS estimates. However, as discussed as in Section 3, these results are likely inconsistent and should be interpreted with caution. In addition to obtaining parameter estimates, I also inspected the residuals of the TSLS models visually and using the Durbin Watson test. Neither provided evidence of serial correlation. Therefore, as discussed in Section 3, the TSLS parameter estimates should be consistent.

The TSLS results for estimating model 1 for soybean growers are reported in table 3.6 in column 5. I find that higher glyphosate application rates for soybean growers in previous periods are associated with decreases in glyphosate application rates over subsequent periods. Specifically, I find that a 1-pound increase in the mean glyphosate application rate in period t-1 is associated with a mean decrease in the glyphosate application rate of 0.38 pounds per acre (p<0.05), holding everything else equal.
Similarly, the TSLS results for model 2 for soybean growers are reported in table 3.7 in column 5. Again, I find that higher glyphosate application rates for soybean growers in previous periods are associated with decreases in glyphosate application rates over subsequent periods. Specifically, I find that a 1-pound increase in the mean glyphosate application rate in period t-1 is associated with a decrease in the mean glyphosate application rate of 55 percent (p<0.01) between period t-1 and t, holding everything else equal. Together, the sign and statistical significance of results from model 1 and model 2 suggest that soybean growers respond to decreases in the susceptibility stock by lowering their glyphosate application rates.

3.6. Conclusions

How do soybean and corn growers respond to declines in glyphosate susceptibility? The results of this study suggest that they respond by using less glyphosate. From a public policy perspective, this result is important because it suggests that the spread of glyphosate resistance should slow over time as growers use less and less glyphosate.

However, it is important to interpret these results carefully. In particular, the dataset used in this study primarily covered a time before GR weeds had been identified in the US. As a result, it is unlikely that the behavior being observed is driven by declines in the marginal productivity of glyphosate. Instead, this could be taken as evidence that growers were responding to the rising marginal user cost described in Section 3.2. If this is the case, these results would suggest that cotton and soybean growers across the US are forward-
looking profit maximizers. This would be consistent with results from Clark and Carlson (1990), which suggest that growers effectively “own” their own weed populations and that there is no tragedy of the commons problem associated with weed management.

3.7. Figures and Tables

Heap (2013)
Figure 3.1. Confirmed glyphosate-resistant weed populations in North America
Figure 3.2. Static Profit-Maximizing Level of Herbicide Application

Figure 3.3. Lifetime Profit-Maximizing Level of Herbicide Application
Figure 3.4. Profit-Maximizing Timepath with Conventional Production Function

Figure 3.5. Cotton Grower Glyphosate Application Rates and Mean Glyphosate Prices
Figure 3.6. Soybean Grower Glyphosate Application Rates and Mean U.S. Glyphosate Prices

Figure 3.7. States included in Cotton Panel Dataset
Figure 3.8. States included in Soybean Panel Dataset

Figure 3.9. Linear Relationship between glyphosate application rates in period t-1 (horizontal axis) and the difference between glyphosate application rates in t and t-1 (vertical axis) for U.S. Cotton growers
Figure 3.10. Linear Relationship between glyphosate application rates in period t-1 (horizontal axis) and the difference between glyphosate application rates in t and t-1 (vertical axis) for U.S. Soybean growers.
Table 3.1. Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Abbreviation</th>
<th>Number of Observations</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cotton Growers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Glyphosate Application</td>
<td>$G_{it}$</td>
<td>41</td>
<td>1.1</td>
<td>0.3</td>
</tr>
<tr>
<td>Rate (lbs/acre)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output Prices</td>
<td>$P_{it}$</td>
<td>41</td>
<td>0.7</td>
<td>0.1</td>
</tr>
<tr>
<td>($2010/lb)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Soybean Growers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Glyphosate Application</td>
<td>$G_{it}$</td>
<td>74</td>
<td>0.9</td>
<td>0.1</td>
</tr>
<tr>
<td>Rate (lbs/acre)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output Prices</td>
<td>$P_{it}$</td>
<td>74</td>
<td>416.6</td>
<td>91.7</td>
</tr>
<tr>
<td>($2010/lb)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Input Prices</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Items Used for Production</td>
<td>$q_t$</td>
<td>6</td>
<td>80.8</td>
<td>3.1</td>
</tr>
<tr>
<td>Price Index (2010=100)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Glyphosate Market Price</td>
<td>$w_t$</td>
<td>6</td>
<td>64.5</td>
<td>10.6</td>
</tr>
<tr>
<td>($2010/lb)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cotton Growers</td>
<td>Soybean Growers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------------------------</td>
<td>----------------</td>
<td>-----------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Controls</td>
<td>Controls</td>
<td>Controls</td>
<td>Controls</td>
</tr>
<tr>
<td></td>
<td>Excluded</td>
<td>Included</td>
<td>Excluded</td>
<td>Included</td>
</tr>
<tr>
<td>Two-Period Lagged</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Glyphosate Application</td>
<td>0.80***</td>
<td>0.69***</td>
<td>0.39***</td>
<td>0.37***</td>
</tr>
<tr>
<td>Rate ((G_{it-2}))</td>
<td>(0.115)</td>
<td>(0.147)</td>
<td>(0.066)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>First difference of</td>
<td>-0.011</td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>U.S. market price for</td>
<td>(0.005)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>glyphosate ((\Delta w_t))</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First difference of</td>
<td>1.43</td>
<td>&lt;0.01**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cotton prices received by</td>
<td>(0.781)</td>
<td>(&lt;0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>growers ((\Delta P_{it}))</td>
<td>(0.005)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>First difference of</td>
<td>.77</td>
<td>1.71**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production Price index</td>
<td>(1.345)</td>
<td>(0.050)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>((\Delta q_t))</td>
<td>.302**</td>
<td>0.47**</td>
<td>.566***</td>
<td>.541***</td>
</tr>
<tr>
<td>Constant</td>
<td>(0.084)</td>
<td>(0.135)</td>
<td>(.065)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>Observations</td>
<td>35</td>
<td>35</td>
<td>68</td>
<td>68</td>
</tr>
<tr>
<td>F test of excluded</td>
<td>48.06</td>
<td>22.12</td>
<td>34.54</td>
<td>26.32</td>
</tr>
<tr>
<td>instruments</td>
<td>*** p&lt;0.001, ** p&lt;0.01, * p&lt;0.05</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3.3. First-Stage Results from Model 2 Estimation

<table>
<thead>
<tr>
<th>Dependent Variable: Lagged Glyphosate Application Rate ($G_{it-1}$)</th>
<th>Cotton Growers</th>
<th>Soybean Growers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Excluded Controls</td>
<td>Included Controls</td>
</tr>
<tr>
<td>Two-Period Lagged Glyphosate Application Rate ($G_{it-2}$)</td>
<td>.80***</td>
<td>0.76***</td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td>(0.167)</td>
</tr>
<tr>
<td>First difference of natural log of U.S. market price for glyphosate $\Delta \ln(w_t)$</td>
<td>-0.011</td>
<td>-0.46</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.173)</td>
</tr>
<tr>
<td>First difference of natural log of cotton prices received by growers $\Delta \ln(P_{it})$</td>
<td>1.43</td>
<td>.704</td>
</tr>
<tr>
<td></td>
<td>(0.781)</td>
<td>(.465)</td>
</tr>
<tr>
<td>First difference of Production Price index $\Delta \ln(q_t)$</td>
<td>.77</td>
<td>.374</td>
</tr>
<tr>
<td></td>
<td>(1.345)</td>
<td>(1.22)</td>
</tr>
<tr>
<td>Constant</td>
<td>.302**</td>
<td>0.47**</td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>Observations</td>
<td>35</td>
<td>35</td>
</tr>
<tr>
<td>F test of excluded instruments</td>
<td>48.06</td>
<td>22.59</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05
Table 3.4. Model 1 Estimates for Cotton Growers

Dependent Variable: First Difference of Glyphosate Application Rate ($\Delta G_{it}$)

<table>
<thead>
<tr>
<th></th>
<th>Estimator: OLS</th>
<th>Controls Excluded</th>
<th>Controls Included</th>
<th>Estimator: TSLS</th>
<th>Controls Excluded</th>
<th>Controls Included</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged Glyphosate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Application Rate ($G_{it-1}$)</td>
<td>-0.32**</td>
<td>-0.42*</td>
<td>-0.24</td>
<td>-0.46*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.147)</td>
<td>(0.159)</td>
<td>(0.199)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>First difference of</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>U.S. market price</td>
<td></td>
<td>-0.01</td>
<td>-0.01</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>for glyphosate ($\Delta w_t$)</td>
<td></td>
<td>(0.012)</td>
<td>(0.013)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First difference of</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cotton prices received by</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>growers ($\Delta P_{it}$)</td>
<td></td>
<td>0.69</td>
<td>1.03</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.506)</td>
<td>(1.245)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First difference of</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production Price index</td>
<td></td>
<td>1.74</td>
<td>2.61</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>($\Delta q_t$)</td>
<td></td>
<td>(1.687)</td>
<td>(1.778)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.45***</td>
<td>0.61*</td>
<td>0.36*</td>
<td>0.68**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
<td>(0.221)</td>
<td>(0.141)</td>
<td>(0.221)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>41</td>
<td>41</td>
<td>35</td>
<td>35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.102</td>
<td>0.069</td>
<td>0.101</td>
<td>0.144</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05
Table 3.5. Model 2 Estimates for Cotton Growers

Dependent Variable: Natural Log First Difference of Glyphosate Application Rate ($\ln(\Delta G_{it})$)

<table>
<thead>
<tr>
<th></th>
<th>Estimator: OLS</th>
<th>Estimator: TSLS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Controls Excluded</td>
<td>Controls Included</td>
</tr>
<tr>
<td>Lagged Glyphosate Application Rate ($G_{it-1}$)</td>
<td>-0.49** (0.106)</td>
<td>-0.54** (0.116)</td>
</tr>
<tr>
<td>First difference of natural log of U.S. market price for glyphosate $\Delta \ln(w_t)$</td>
<td>-0.11 (0.636)</td>
<td>-0.10 (0.642)</td>
</tr>
<tr>
<td>First difference of natural log of cotton prices received by growers $\Delta \ln(P_{it})$</td>
<td>0.20 (0.751)</td>
<td>0.43 (0.550)</td>
</tr>
<tr>
<td>First difference of Production Price index $\Delta \ln(q_t)$</td>
<td>1.56 (1.177)</td>
<td>2.35 (1.505)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.61*** (0.117)</td>
<td>0.70** (0.152)</td>
</tr>
<tr>
<td>Observations</td>
<td>41</td>
<td>41</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.230</td>
<td>0.204</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05
Table 3.6. Model 1 Estimates for Soybean Growers
Dependent Variable: First Difference of Glyphosate Application Rate ($\Delta G_{it}$)

<table>
<thead>
<tr>
<th></th>
<th>Estimator: OLS</th>
<th>Estimator: TSLS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Controls</td>
<td>Controls</td>
</tr>
<tr>
<td>Lagged Glyphosate Application Rate ($G_{it-1}$)</td>
<td>-0.64***</td>
<td>-0.61***</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.118)</td>
</tr>
<tr>
<td>First difference of U.S. market price for glyphosate ($\Delta w_t$)</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>First difference of soybean prices received by growers ($\Delta P_{it}$)</td>
<td>&lt;0.01**</td>
<td>&lt;0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>First difference of Production Price index ($\Delta q_t$)</td>
<td>-5.17***</td>
<td>-5.46***</td>
</tr>
<tr>
<td></td>
<td>(1.091)</td>
<td>(1.079)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.62***</td>
<td>0.58***</td>
</tr>
<tr>
<td></td>
<td>(0.096)</td>
<td>(0.104)</td>
</tr>
<tr>
<td>Observations</td>
<td>74</td>
<td>74</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.394</td>
<td>0.530</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
Table 3.7. Model 2 Estimates for Soybean Growers
Dependent Variable: First Difference of Natural Log of Glyphosate Application Rate ($\Delta \ln(G_{it})$)

<table>
<thead>
<tr>
<th></th>
<th>Estimator: OLS</th>
<th></th>
<th>Estimator: TSLS</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Controls</td>
<td>Controls</td>
<td>Controls</td>
<td>Controls</td>
</tr>
<tr>
<td></td>
<td>Excluded</td>
<td>Included</td>
<td>Excluded</td>
<td>Included</td>
</tr>
<tr>
<td>Lagged Glyphosate Application Rate ($G_{it-1}$)</td>
<td>-0.76***</td>
<td>-0.73***</td>
<td>-0.49*</td>
<td>-0.55**</td>
</tr>
<tr>
<td></td>
<td>(0.143)</td>
<td>(0.145)</td>
<td>(0.208)</td>
<td>(0.209)</td>
</tr>
<tr>
<td>First difference of natural log of U.S. market price for glyphosate $\Delta \ln(w_t)$</td>
<td>-0.36</td>
<td></td>
<td>-0.28</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.192)</td>
<td></td>
<td>(0.195)</td>
<td></td>
</tr>
<tr>
<td>First difference of natural log of soy prices received by grower $\Delta \ln(P_{it})$</td>
<td>0.75***</td>
<td></td>
<td>0.78***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.184)</td>
<td></td>
<td>(0.179)</td>
<td></td>
</tr>
<tr>
<td>First difference of Production Price index $\Delta \ln(q_t)$</td>
<td>-3.60***</td>
<td></td>
<td>-3.68***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.694)</td>
<td></td>
<td>(0.801)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.74***</td>
<td>0.69***</td>
<td>0.49**</td>
<td>0.54**</td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.131)</td>
<td>(0.186)</td>
<td>(0.184)</td>
</tr>
<tr>
<td>Observations</td>
<td>74</td>
<td>74</td>
<td>68</td>
<td>68</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.431</td>
<td>0.545</td>
<td>0.330</td>
<td>0.510</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
3.8 References


Western Farm Press. “Glyphosate prices skyrocket on short supplies”. Available at <http://westernfarmpress.com/glyphosate-prices-skyrocket-short-supplies>


APPENDICES
A.1 Exogenous Herbicide Susceptibility

An alternative method of modeling herbicide application decisions is proposed by Lichtenberg and Zilberman (1985). They argue that damage control agents like glyphosate should not be modeled as normal inputs as they were above because they do not enhance productivity directly like standard types of production factors (these inputs can in fact impede production since herbicides can be harmful to crop plants). Instead, herbicides contribute to actual (realized) production by eliminating weeds that would destroy potential output. As a result, the productive contribution of herbicides is bounded in a particular way. For example, if no herbicides are applied to a field, this implies that 0 percent of the weed population would be eliminated and at most 100 percent of the crop would be lost. Similarly, if herbicides are applied to a field, then the most abatement it could achieve is 100 percent elimination of the weed population and thus 0 percent of the crop would be lost.

Lichtenberg and Zilberman propose a damage abatement function, which I define here as abatement function $A(X)$ as the proportion of the destructive capacity of the damaging agent eliminated by the application of a level of herbicide $X$. This function translates herbicide application into the proportion of the target population killed by the application. This definition suggests that the abatement function will possess the properties of a cumulative probability distribution: It will be defined on the $(0, 1)$ interval with $A = 1$ denoting complete eradication of the weed population and $A = 0$ denoting no weeds eliminated (i.e. maximum destructive capacity). Similarly, the function will be monotonically
increasing and it will approach a value of unity as damage-control agent use increases.

Therefore, the new production can be defined as follows:

$$ Y_t = F[X_t, A(G_t, S_t)] $$

(A.1)

where $Y_t$ is output produced at time $t$, and $X_t$ is an aggregate of non-glyphosate inputs, $A(G_t, S_t)$ the fraction of weeds eliminated by herbicide application, $G_t$ the amount of glyphosate applied at time $t$, and $S_t$ is the herbicide susceptibility stock at time $t$. In addition, the following are assumed:

$$ \frac{\partial F}{\partial X_t} > 0, \frac{\partial A}{\partial S_t} > 0, \text{ and } \frac{\partial A}{\partial G_t} > 0. $$

In other words, the more $G_t$ and $S_t$ the more weeds are eliminated.

Given this new production function, the profit maximization problem solved by the farm owner now becomes:

$$ \max_{\{G_t\}} \pi_t = PF[\bar{X}, A(G_t, S_t)] - wG_t - q\bar{X} $$

(A.2)

Again assuming that all other inputs are fixed at $\bar{X}$, the first and second-order conditions for the profit-maximization problem are:

$$ \text{FOC: } \frac{\partial \pi}{\partial G_t} = P \frac{\partial F}{\partial A} \frac{\partial A}{\partial G_t} - w = 0 $$

(A.3)

$$ \text{SOC: } \frac{\partial^2 \pi}{\partial G_t^2} = P \frac{\partial^2 F}{\partial A_t^2} \left( \frac{\partial A}{\partial G_t} \right)^2 + P \frac{\partial F}{\partial A} \frac{\partial^2 A}{\partial G_t^2} < 0 $$

(A.4)

Once again the profit maximization level of herbicide use is found where the marginal value product equals the marginal cost. Note, however, because $A(G_t, S_t)$ possesses the properties of a cumulative probability distribution, the derivative of $A(G_t, S_t)$ with respect to $G_t$ is simply the density of $A(G_t, S_t)$. In other words, the marginal value product of the herbicide will take on the characteristics of a probability density function.
Figure 5 illustrates the optimal herbicide application rate where the marginal productivity function is drawn to resemble a normal probability density function. Note that the region of optimal herbicide application is exclusively on the downward sloping portion of the marginal productivity function.

Using figure A.1, one can easily how growers will respond to declines in the susceptibility stock under this model. For example, suppose \( S_t \) decreases, then given the assumptions listed above a farmer would need to apply more herbicide to kill the same proportion of weeds as before. This will be represented in by the marginal productivity function skewing to the right (see figure A.2). If one assumes that this bimodal distribution whose shape is not dramatically changed by the decrease in \( S \), as is drawn in A.1, it can be seen that the downward sloping portion of the marginal productivity function has shifted outward. As a result, the optimal herbicide application rate increases as the susceptibility stock declines. A more formal derivation of this result can be found in Lichtenberg and Zilberman (1985).
A.2 Figures and Tables

Figure A.1. Profit-Maximizing Level of Herbicide Application

Modified from Zilberman (1985)

Figure A.2. Consequences of Decline in Susceptibility Stock