# HEALTH BURDEN ASSOCIATED WITH TILLAGE-RELATED $PM_{2.5}$ POLLUTION IN THE UNITED STATES, AND OPTIMAL SUBSIDY TO PROMOTE CONSERVATION TILLAGE

By

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## ABSTRACT

Exposure to airborne particulate matter of diameter less than 2.5 microns ($PM_{2.5}$) is associated with cardiovascular diseases (CVD) and chronic obstructive pulmonary disease (COPD). In agriculture, the practice of tilling generates $PM_{2.5}$ emissions that can jeopardize human health. In this work, we estimated the annual deaths from CVD and COPD attributable to $PM_{2.5}$ emissions from corn, soybean, cotton, and wheat tillage in the contiguous United States using data from the Environmental Protection Agency's National Emissions Inventory, the Institute of Health Metrics and Evaluation's global burden of risk factors study, the US decennial Census, and the US Centers for Disease Control. We developed and implemented a conceptual framework for identifying the optimal subsidy upon accounting for health benefits arising from reducing conventional tillage. We estimated that approximately 1,000 annual deaths from CVD and 300 annual deaths from COPD were attributable to tillage-related $PM_{2.5}$ emissions; and about 360 annual deaths can be reduced upon a shift from conventional to conservation tillage. We calculated that the optimal per acre subsidy for a change from conventional to conservation tillage for soybean planting in Iowa considering the reduction only in CVD and COPD deaths is 16.3 US dollars per acre. We discussed agricultural policies and on-farm measures that promote conservation tillage and $PM_{2.5}$ emissions reduction such as subsidies for adopting conservation tillage, carbon capture credits, planting of cover crops, use of windbreaks, use of alternative herbicides, use of herbicide-tolerant crops and protection of the herbicide-tolerance trait in crops.

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TABLE OF CONTENTS

## **Chapter 1**: Estimating public health burden of tillage-related $PM_{2.5}$ emissions in the contiguous United States

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### 1.1 Introduction

An air pollutant is any airborne, respirable substance that may harm humans, animals, vegetation or materials; and in humans may contribute to an increase in illness or present a potential hazard (Kampa & Castanas, 2008). Air pollutants are generally classified as gaseous pollutants such as nitrogen oxides; organic pollutants such as dioxins; heavy metals pollutants such as lead; and particulate matter (PM), which is complex and varying mixture of particles suspended in the air (Kampa & Castanas, 2008). Particulate matter 2.5 ($PM_{2.5}$) is defined as particles with a diameter of 2.5 microns or smaller (U.S. Environmental Protection Agency, 2021b). $PM_{2.5}$ can be categorized into primary and secondary emissions. Primary $PM_{2.5}$ emissions are emitted directly from industrial, residential, vehicle and agricultural sources among others; while secondary $PM_{2.5}$ includes emissions of precursor compounds such as sulfur oxides, nitrogen oxides, and ammonia compounds that later form $PM_{2.5}$ particles (Fine et al., 2008). $PM_{2.5}$ can remain in the atmosphere from a few days to a week and can travel hundreds of miles, depending on conditions such as wind direction and speed, deposition velocities and altitude of particles (Gugamsetty et al., 2012; Wang et al., 2017).

$PM_{2.5}$ poses a significant human health risk as it can enter deep into the human lungs when inhaled, deposit in alveoli, enter pulmonary circulation and likely the systematic circulation (Wu et al., 2018). $PM_{2.5}$ pollution has been linked to various health issues such as stroke, ischemic heart disease, chronic obstructive pulmonary diseases, lung cancer, asthma, breathing difficulties, coughing, irritation in respiratory tract, heart attacks, and others (Bu et al., 2021). In the United States (US), interest in the health effects of $PM_{2.5}$ pollution increased after large cohort studies showed significant positive associations between $PM_{2.5}$ exposure and mortality. A large prospective cohort study with about 8000 adults from six cities in the United States, followed for a period of about 15 years, found a significant difference between the adjusted mortality rate ratios from cardiopulmonary diseases between the most $PM_{2.5}$ polluted city i.e. Steubenville, Ohio versus the least polluted city i.e. Portage, Wisconsin (Dockery et al., 1993). Another cohort study of about 550,000 adults in 151 US metropolitan areas found a significant difference in adjusted risk ratios (RR: 1.17; 95% CI: 1.09, 1.26) for all-cause mortality between most $PM_{2.5}$ polluted areas versus the least polluted areas (Pope et al., 1995). Studies in the rural areas of the United States have also shown an association between $PM_{2.5}$ emissions and mortality. A cohort study by Weichenthal et al. (2014) observed positive associations between $PM_{2.5}$ and cardiovascular mortality in men, with strength of association increasing for the participants who did not change their place of residence during the study period, highlighting the long-term health impacts of $PM_{2.5}$ exposure in rural agricultural areas in the United States. Another study on the long-term effect of $PM_{2.5}$ on mortality among elderly population in both rural and urban California found significant associations between $PM_{2.5}$ and all-cause mortality and cause-specific mortality such as cardiovascular diseases (Garcia et al., 2016). Similarly, Moran et al. (2014) found high level of $PM_{2.5}$ exposure among agricultural workers involved in almonds, tomatoes and melon farming.

Epidemiological studies provide strong evidence of an association between $PM_{2.5}$ inhalation and cardiovascular diseases (CVD) (Dominici et al., 2006; Feng et al., 2016; Hayes et al., 2020) and chronic obstructive pulmonary diseases (COPD) (Gan et al., 2013; Zhu et al., 2020). For instance, an increase in $PM_{2.5}$ by 10 $\mu g/m^3$ was associated with an increase of cardiovascular deaths by about 4.7% (Kim et al., 2020). Significant public health costs are associated with $PM_{2.5}$ emissions. A standard deviation increase in the daily average $PM_{2.5}$ level increased coronary obstructive pulmonary disease and asthma related expenses by 12.7%, with an estimated value of 9 billion United States Dollars (USD) (Williams & Phaneuf, 2019). In 2002 in the United States it was estimated that $PM_{2.5}$, despite constituting only 6% of the total emissions including emissions from five other pollutants such as ammonia ($NH_3$) and sulfur dioxide ($SO_2$), made up 23% of the total gross annual human health damage; and the damage was valued at 17 billion USD (Muller & Mendelsohn, 2007). Increases in local $PM_{2.5}$ levels lead to more emergency room visits, more hospitalizations and higher inpatient costs in the elderly US population aged 65 and above; and the overall decrease in the average US $PM_{2.5}$ level by 4.9 $\mu g/m^3$ between 1999 and 2013 has resulted in an annual mortality reduction benefit of 24 billion USD (Deryugina et al., 2019). A study in the contiguous United States estimated that the marginal social cost of primary $PM_{2.5}$ was between USD 88,000- 130,000 per a ton of emissions and were higher than $PM_{2.5}$ precursors such as sulfur oxides and nitrogen oxides (Heo et al., 2016). The same study estimated that the aggregate annual social cost of primary $PM_{2.5}$ was about USD 330 billion.

Agricultural activities such as tillage, crop harvest, fertilizer and pesticide use, fuel use, livestock operations, and crop residue burning are key sources of PM emissions (Chen et al., 2017). Globally, the agriculture sector is the second largest anthropogenic source contributor to mortality attributable with $PM_{2.5}$ pollution, accounting for one-fifth of the total mortality; and for context, residential and commercial energy use, such as the use of biofuel in cooking, is the largest contributor and power generation by fossil fuel fired power plants is the third largest contributor (Lelieveld et al., 2015). In the Eastern United States, agriculture is the largest anthropogenic source category of $PM_{2.5}$ emissions (Lelieveld et al., 2015). Pozzer et al. (2017) found that a reduction in agricultural emissions by 50% would reduce mortality by 16,000 people per year in North America. Similarly, a 50% reduction in agricultural emissions in the United States was associated with 28% reduction in health costs with 15,000 fewer deaths and a reduction in health economic costs by about 66 billion USD in 2010 (Giannadaki et al., 2018).

Among the agricultural activities, tillage is one such practice that leads to primary $PM_{2.5}$ emissions. Agricultural tillage is a universal practice of physically turning the soil surface, mainly to prepare for planting crops, controlling weed growth, incorporating manure or fertilizer into the soil, and mixing crop residue into soil (Claassen et al., 2018). Physical turning of the soil during tillage results in mechanical disturbance and disintegration of soil particles (Chen et al., 2017); and, consequently emissions of dust containing primary $PM_{2.5}$ that adversely affects human health (Domingo et al., 2021). Negative environmental effects of intensive tillage often include soil erosion, soil moisture loss, and nutrient runoff to water source where the degree of impact depends on the tillage system used (Lal, 2015; Sun et al., 2015). Understanding the need to mitigate the negative effects of tillage mainly on soil health, agriculturists started to develop tillage systems and technologies aimed at reducing soil erosion and protecting soil health (Triplett & Dick, 2008). Generally based on the type of soil disturbance and soil cover, the tillage systems are classified into three types: conventional tillage, conservation tillage, and no-tillage. Conventional tillage, plowing and overturning soil deeply, causes higher soil disturbances and leaves less than 30% crop residue, consequently causing higher soil erosion (N. Uri et al., 1998). Conservation tillage system is defined as a tillage system that retains at least 30% of the crop residue cover at planting (Claassen et al., 2018) and conservation tillage variants such as mulch till or strip till disturb the soil less than conventional tillage. Conservation tillage variants are defined based on the soil tillage intensity rating (STIR) numerical index that measures type and severity of soil disturbance; and is ranged between 0 to 200 with higher values indicating higher tillage intensity (Claassen et al., 2018). Mulch till uses implements such as chisels and disks but has low soil disturbances with STIR value less than 80 (Claassen et al., 2018). Similarly, strip till is a form of mulch till, with a STIR value of less than 80, used for row crops where only narrow strips of land are tilled. No-tillage is the absence of tillage operations between the prior crop’s harvest and the current crop’s harvest and usually has a STIR value less than 30. As minimum or no soil disturbance occurs, there is negligible soil erosion and consequently minimum $PM_{2.5}$ emissions from a no-tillage system.

Although the relationship between agricultural emissions and public health have been studied, most inquiries have focused on PM emissions from crop residue burning, fertilizers, and pesticide use; and very few have focused on the effect of tillage on primary $PM_{2.5}$ emissions and consequently on public health. We are aware of one paper that directly addresses this issue where the authors estimated the relationship between no-tillage adoption in soybean crop and the reduction in $PM_{2.5}$ emissions in the US Corn Belt (Behrer and Lobell 2022). In this chapter, we aim to fill the knowledge gap in tillage-related $PM_{2.5}$ emissions and public health burden in the contiguous USA by estimating the primary $PM_{2.5}$ emissions from tillage from four widely planted crops in the US: corn, soybean, wheat, and cotton. Then, we estimate mortality and disability-adjusted life years (DALYs) due to cardiovascular diseases (CVD) and COPD attributable to tillage related primary $PM_{2.5}$ emissions. We also quantify the health economic loss from such emissions and quantify the benefits of reduction in $PM_{2.5}$ emissions when shifting from conventional to conservation tillage practice.

## 1.2 Methods

We use two separate data sources to first determine the primary $PM_{2.5}$ emissions from crop-tillage combinations and then to determine the annual deaths and DALYs associated with $PM_{2.5}$ emissions from crop-tillage combinations.

### 1.2.1 Primary $PM_{2.5}$ emissions from crop-tillage combination

$PM_{2.5}$ emissions from crop tillage were calculated using values obtained from the United States Environmental Protection Agency's National Emissions Inventory (NEI) of 2017 (U.S. Environmental Protection Agency, 2021a). NEI 2017 provided data on tillage type, tillage passes, tillage acres, crop type, crop acres and soil silt percent; and we used NEI 2017 methodology to calculate $PM_{2.5}$ emissions for crop-tillage combinations at the county level. Soil silt percent was used to measure dust emissions from soil preparation operations as recommended by EPA (Carvacho et al., 2004). In addition, we used the NEI 2017 data to calculate total $PM_{2.5}$ emissions from all sources at the county level. Detailed methodology on $PM_{2.5}$ emissions calculation is outlined in the EPA's National Emissions Inventory Support Document (U.S. Environmental Protection Agency, 2021a). In brief, the steps are summarized below.

State-level data on the total acres of conventional, conservation and no-till land area were available, and we calculated the ratio of each tillage acre. This ratio was then multiplied by total crop acreage to obtain the crop area harvested under each tillage type for each county. This process is summarized as (U.S. Environmental Protection Agency, 2021a):

(1) $a_{t,\mathrm{x},\mathrm{c}} = r_{c,t} \times a_{c,x}$

where $a_{t,c,x}$ represents the total agricultural land tilled (in acres) by tillage type $t$ (i.e., conventional, conservational tillage or no tillage) and crop type $x$ (i.e., corn or soybean or wheat or cotton) in county $c$; $r_{c,t}$ represents the ratio of tillage acres of crop type $t$ in county $c$; and $a_{c,x}$ represents the acres of crop type $x$ harvested in county $c$.

Separately, we calculated the county-level $PM_{2.5}$ emissions factor specific to crop and tillage type as:

(2) $EF_{t,\,x,\,c} = C \times k \times sc^{0.6} \times p_t$,

where $EF_{t,\,x,\,c}$ represents the emissions factor for $PM_{2.5}$ emissions in lbs./acre for tillage type $t$, and crop type $x$ in county $c$; $C$ denotes a constant parameter of 4.8 lbs./acre-pass as defined in NEI 2017 methodology; $k$ denotes the dimensionless particle size multiplier for $PM_{2.5}$ and is equal to 0.042; $sc$ represents the percent silt content of surface soil in county $c$, defined as the mass fraction of particles smaller than 50 μm diameter found in surface soil; and $p_t$ represents the number of passes or tilling events in a year by tillage type $t$. The number of passes $p_t$ in conventional tillage vs. conservation tillage for corn, soybean, wheat and cotton were, respectively, 2 vs. 1, 2 vs. 1, 5 vs. 3 (generally), and 8 vs. 5 (generally).

Finally, we used equations (1) and (2) to calculate the county-level $PM_{2.5}$ emissions from tillage as:

(3) $EM_{t,x,c} = EF_{t,x,c} \times\ a_{t,x,c} \times \frac{1\ ton}{2{,}000\ lbs}$,

where $EM_{t,x,c}$ is the annual $PM_{2.5}$ emissions from a crop-tillage combination (tillage type $t$ and crop type $x$) in county $c$. To express the annual $PM_{2.5}$ emissions in tons/acre, equation (3) includes a conversion multiplier of 1 ton/2,000 lbs. While calculating the emissions from each crop-tillage combination, we assumed that no-tillage caused zero $PM_{2.5}$ emissions for all four crops because no-tillage involves minimum physical disturbance of the soil and hence has negligible $PM_{2.5}$ emissions.

### 1.2.2 Annual deaths and DALYs due to CVD and COPD

At the state level, we used data on $PM_{2.5}$ related annual deaths and DALYs from CVD and COPD from the Institute for Health Metrics and Evaluation's (IHME) global burden of risk factors study (Abbafati et al., 2020).

The state level death and DALYs numbers were due to $PM_{2.5}$ pollution from all sources, not just tillage. Hence, to impute deaths and DALYs at the county level, CVD death rate, COPD prevalence rates provided by the US Centers for Disease Control (CDC) and county level population estimates from the US census of 2020 were used.

1.2.2.1 Mortality and DALYs data imputation at the county level

The US census 2020 provided data on the county level population estimates (U.S. Census Bureau, 2022). We obtained 2018-2020 county level CVD deaths per 100,000 data from the CDC's Interactive Atlas of Heart Disease and Stroke (CDC, accessed 2023). This prevalence rate was multiplied by the county level population to calculate the estimated number of CVD deaths in a county. This is summarized as:

(4) $CVD\ deaths_c = \ CVD\ rate_c \times Popn_c$,

where $CVD\ deaths_c$ is the estimated CVD deaths for county $c$; $CVD\ rate_c$ is the age-standardized CVD rate per 100,000 for county $c$; and $Popn_c$ is the population estimate for county $c$.

Then the ratio of CVD deaths was calculated as

(5) $Ratio\ CVD_c = \ CVD\ deaths_c / \sum_{c=1}^{C} CVD\ deaths_c$,

where $Ratio\ CVD_c$ is the ratio of CVD deaths in county $c$ to the total CVD deaths when summed across all counties in the state. Finally, CVD deaths specific to $PM_{2.5}$ at the county level were imputed from multiplying $Ratio\ CVD_c$ by the state level CVD deaths specific to $PM_{2.5}$ pollution as provided by IHME. The same ratio given in equation (5) was used to impute DALYs due to CVD specific to $PM_{2.5}$ at the county level.

Similar steps were used to impute county level COPD deaths. We used county level COPD prevalence and county level population estimates to calculate the estimated number of COPD population in a county as:

(6) $COPD\ popn_c = (COPD\ percent_c/100)\ \times Popn_c$,

where $COPD\ popn_c$ is the estimated number of people with COPD in a county *c*; $COPD\ percent_c$ is the percent of population with COPD in county *c*; and $Popn_c$ is the population estimate for county *c*. Then the ratio of people with COPD was calculated as

(7) $Ratio\ COPD_c =\ COPD\ popn_c/\sum_{c=1}^{C} COPD\ popn_c$,

where $Ratio\ COPD_c$ is the ratio of the number of people with COPD in a county *c* over the total number of people with COPD when summed across all counties in the state. Finally, COPD deaths specific to $PM_{2.5}$ at the county level were imputed from multiplying $Ratio\ COPD_c$) by the state level COPD deaths specific to $PM_{2.5}$ pollution as provided by IHME.

<u>1.2.2.2 Calculation of deaths and DALYs due to crop-tillage combination at the county level</u>

We now have imputed estimates of deaths and DALYs due to CVD and COPD resulting only from $PM_{2.5}$ emissions. Likewise, we also have estimates of both the total $PM_{2.5}$ emissions from all sources and estimates of $PM_{2.5}$ emissions from each crop-tillage combination at the county level. Hence, we calculated the deaths attributable to a crop-tillage combination by multiplying the imputed deaths at the county level with the ratio of emissions from a crop-tillage combination when compared to the total emissions from all sources as follows:

(8) $Deaths\ croptill_{t,x,c} = (E_{\ t,x,c}/E_c)\ \times Imputed\ deaths_c$,

where $Deaths\ croptill_{t,x,c}$ is the estimated annual deaths attributable to $PM_{2.5}$ emissions from a crop-tillage combination (tillage type $t$ and crop type $x$) in county $c$; $E_c$ is the annual $PM_{2.5}$ emissions in county $c$ and $Imputed\ deaths_c$ is the imputed annual deaths due to CVD or COPD at the county $c$. A similar calculation was done for estimating annual DALYs attributable to a crop-tillage combination at the county level.

### 1.2.3 Estimate of health economic loss

To calculate the health economic loss due to deaths we used the value of a statistical life (VSL) metric as 10 million USD (Kniesner & Viscusi, 2019). VSL is an indicator that measures an aggregate of individuals' willingness to pay for a reduction in risk of death and is widely used to monetize health risks associated with air pollution (Giannadaki et al., 2018; Kniesner & Viscusi, 2019). Similarly, DALY is interpreted as a year of life in full health lost due to a disease or condition (Highfill & Bernstein, 2019). A reduction in one DALY is interpreted as a gain of one healthy life year. We used the value of 100,000 USD as the estimate of a year of life in full health similar to a recent study which calculated US health care spending for chronic diseases (Highfill & Bernstein, 2019).

## 1.3 Results

Annual primary $PM_{2.5}$ emissions from soybeans, corn, wheat, and cotton in the contiguous US were estimated to be about 75,000 tons, 73,000 tons, 58,000 tons and 44,000 tons respectively (Table 1.1). This sums to about 0.25 million tons annually

**Table 1.1**: Annual primary $PM_{2.5}$ emissions (in tons) from crop tillage by state.

| State | Soybean tillage | Corn tillage | Wheat tillage | Cotton tillage | Sum from the 4 crops | Emissions from all sources |
|---|---|---|---|---|---|---|
| Alabama | 108 | 128 | 107 | 923 | 1,266 | 102,250 |
| Arizona | 0 | 27 | 137 | 901 | 1,065 | 84,891 |

**Table 1.1**: (cont'd)

| | | | | | | |
|---|---|---|---|---|---|---|
| Arkansas | 4,242 | 956 | 414 | 3,245 | 8,857 | 143,428 |
| California | 0 | 131 | 429 | 1,574 | 2,134 | 455,356 |
| Colorado | 12 | 702 | 2,737 | 0 | 3,451 | 75,822 |
| Connecticut | 1 | 6 | 0 | 0 | 7 | 11,867 |
| Delaware | 77 | 87 | 68 | 0 | 232 | 4,875 |
| Florida | 6 | 22 | 10 | 265 | 302 | 180,635 |
| Georgia | 62 | 215 | 109 | 2,699 | 3,085 | 143,331 |
| Idaho | 0 | 220 | 3,728 | 0 | 3,948 | 204,412 |
| Illinois | 12,112 | 13,113 | 1,646 | 0 | 26,870 | 197,838 |
| Indiana | 4,845 | 4,526 | 546 | 0 | 9,917 | 72,174 |
| Iowa | 8,285 | 11,696 | 20 | 0 | 20,002 | 72,358 |
| Kansas | 3,137 | 3,639 | 4,722 | 143 | 11,641 | 210,397 |
| Kentucky | 994 | 783 | 472 | 0 | 2,249 | 73,380 |
| Louisiana | 1,447 | 640 | 46 | 1,264 | 3,398 | 125,854 |
| Maine | 2 | 9 | 1 | 0 | 12 | 26,356 |
| Maryland | 162 | 148 | 159 | 0 | 468 | 30,037 |
| Massachusetts | 0 | 3 | 0 | 0 | 4 | 25,322 |
| Michigan | 1,958 | 1,743 | 1,238 | 0 | 4,939 | 74,170 |
| Minnesota | 9,208 | 9,565 | 2,830 | 0 | 21,603 | 127,992 |
| Mississippi | 2,838 | 696 | 68 | 3,674 | 7,275 | 98,108 |
| Missouri | 4,887 | 2,630 | 1,037 | 1,454 | 10,008 | 261,619 |
| Montana | 6 | 32 | 3,188 | 0 | 3,226 | 268,184 |
| Nebraska | 2,535 | 5,422 | 1,349 | 0 | 9,306 | 84,933 |
| Nevada | 0 | 11 | 24 | 0 | 35 | 46,285 |
| New Hampshire | 0 | 0 | 0 | 0 | 0 | 11,263 |
| New Jersey | 73 | 64 | 38 | 0 | 174 | 24,475 |
| New Mexico | 0 | 33 | 245 | 196 | 474 | 55,936 |
| New York | 396 | 653 | 414 | 0 | 1,463 | 63,431 |

**Table 1.1**: (cont'd)

| | | | | | | |
|---|---|---|---|---|---|---|
| North Carolina | 926 | 562 | 456 | 854 | 2,798 | 74,384 |
| North Dakota | 5,042 | 1,523 | 6,520 | 0 | 13,085 | 77,630 |
| Ohio | 3,750 | 2,563 | 1,047 | 0 | 7,359 | 89,940 |
| Oklahoma | 574 | 276 | 7,243 | 1,779 | 9,871 | 191,380 |
| Oregon | 0 | 74 | 1,601 | 0 | 1,675 | 304,941 |
| Pennsylvania | 316 | 496 | 254 | 0 | 1,066 | 87,847 |
| Rhode Island | 0 | 0 | 0 | 0 | 0 | 3,474 |
| South Carolina | 142 | 185 | 126 | 541 | 994 | 68,566 |
| South Dakota | 3,723 | 3,517 | 1,054 | 0 | 8,294 | 64,154 |
| Tennessee | 581 | 285 | 254 | 484 | 1,603 | 77,216 |
| Texas | 185 | 2,051 | 5,885 | 23,655 | 31,777 | 345,136 |
| Utah | 0 | 44 | 374 | 0 | 419 | 56,271 |
| Vermont | 5 | 10 | 1 | 0 | 16 | 11,414 |
| Virginia | 165 | 115 | 103 | 160 | 542 | 68,551 |
| Washington | 0 | 99 | 6,474 | 0 | 6,573 | 185,971 |
| West Virginia | 10 | 24 | 5 | 0 | 39 | 39,538 |
| Wisconsin | 1,962 | 2,888 | 377 | 0 | 5,226 | 69,603 |
| Wyoming | 0 | 63 | 252 | 0 | 316 | 66,423 |
| **Total** | **74,774** | **72,673** | **57,806** | **43,811** | **249,063** | **5,239,418** |

Note: Only point estimates were available for emissions. 95% CI were not available.

Emissions from conventional tillage practice was about 151,000 tons, with emissions from soybean crop being the highest among the four crops at estimated emissions of 44,000 tons. While, emissions from conservation tillage practice was about 98,000 tons, with emissions from corn crop being the highest at about 31,000 tons of emissions (Table 1.2).

Primary $PM_{2.5}$ emissions from the four crops were attributed to 1002 deaths (95% CI: 522, 1564) and 21,937 DALYs (95% CI: 11,476, 34,039) from CVD annually (Table 1.3). Similarly, 294 deaths (95% CI: 133, 505) and 7,368 DALYs (95% CI: 3,418, 12,419) from COPD annually were attributed to emissions from the four crops (Table 1.4). Hence, total estimated annual deaths from both CVD and COPD attributable to primary $PM_{2.5}$ from crops was 1,296 deaths, see Figure 1.1 for the spatial distribution of deaths.

**Table 1.2**: Estimated primary $PM_{2.5}$ emissions for crop-tillage combination.

| | **Emissions from Conventional tillage (tons)** | **Emissions from Conservation tillage (tons)** | **Total emissions from both tillage (tons)** |
|---|---:|---:|---:|
| Soybean | 44,206 | 30,568 | 74,774 |
| Corn | 41,182 | 31,491 | 72,673 |
| Wheat | 36,157 | 21,649 | 57,806 |
| Cotton | 29,560 | 14,250 | 43,810 |
| **Total** | **151,105** | **97,958** | **249,063** |

**Table 1.3**: Annual CVD deaths and DALYs attributable to primary $PM_{2.5}$ emissions from each crop-tillage combination.

| | Deaths attributable to | | | DALYs attributable to | | |
|---|---|---|---|---|---|---|
| | **Conventional tillage (95% CI)*** | **Conservation tillage (95% CI)*** | **Both tillage practices (95% CI)*** | **Conventional tillage (95% CI)*** | **Conservation tillage (95% CI)*** | **Both tillage practices (95% CI)*** |
| Soybean | 204 (107, 319) | 147 (77, 228) | 351 (184, 547) | 4,452 (2,325, 6,912) | 3,175 (1,674, 4,904) | 7,627 (3,999, 11,816) |
| Corn | 193 (101, 300) | 142 (74, 221) | 335 (175, 521) | 4,171 (2,190, 6,458) | 3,054 (1,603, 4,724) | 7,225 (3,793, 11,182) |
| Wheat | 89 (44, 142) | 52 (26, 83) | 141 (70, 225) | 1,942 (961, 3,089) | 1,134 (559, 1,807) | 3,076 (1,520, 4,896) |
| Cotton | 120 (65, 184) | 55 (29, 86) | 175 (94, 270) | 2,742 (1,498, 4,182) | 1,267 (666, 1,962) | 4,009 (2,164, 6,144) |
| **Total** | **606 (317, 945)** | **396 (206, 618)** | **1002 (523, 1,563)** | **13,307 (6974, 20,641)** | **8,630 (4,502, 13,397)** | **21,937 (11,476, 34,038)** |

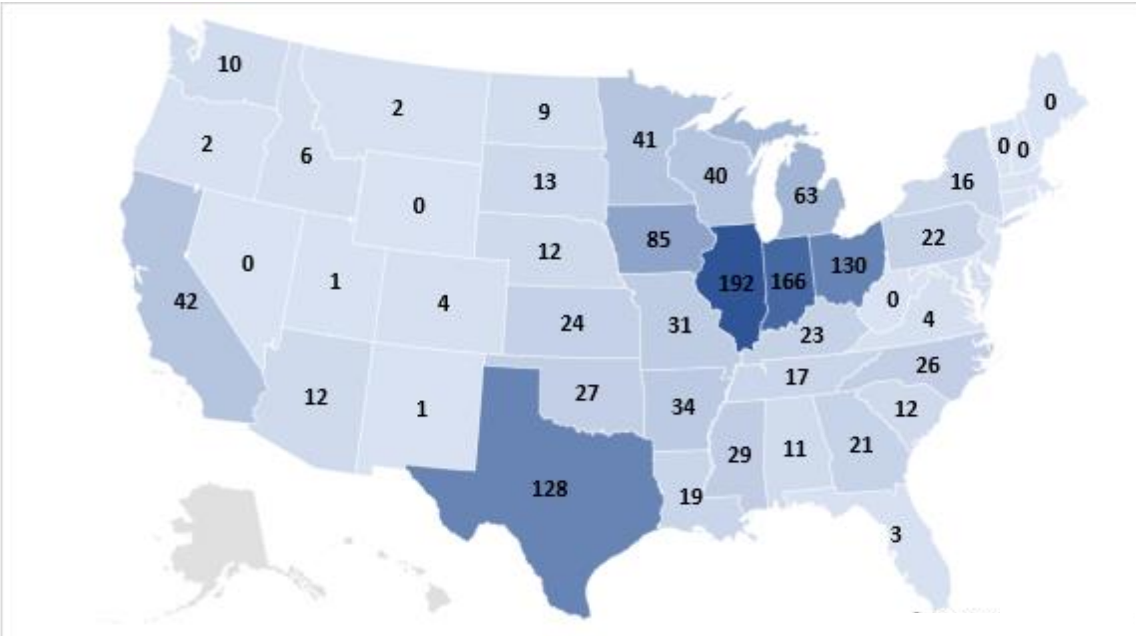
* Note: 95 % CI for deaths were obtained from Abbafati et al. 2020 study only. Point estimates from EPA were assumed to be certain as 95% CI for $PM_{2.5}$ was not available in the data source.

**Table 1.4**: Annual COPD deaths and DALYs attributable to primary $PM_{2.5}$ emissions from each crop-tillage combination.

| | Deaths attributable to | | | DALYs attributable to | | |
|---|---|---|---|---|---|---|
| | **Conventional tillage (95% CI)*** | **Conservation tillage (95% CI)*** | **Both tillage practices (95% CI)*** | **Conventional tillage (95% CI)*** | **Conservation tillage (95% CI)*** | **Both tillage practices (95% CI)*** |
| Soybean | 61 (28, 104) | 44 (20, 75) | 105 (48, 179) | 1,514 (703, 2,551) | 1,089 (511, 1,830) | 2,603 (1,214, 4,381) |
| Corn | 57 (26, 98) | 43 (20, 73) | 100 (46, 171) | 1,439 (672, 2,418) | 1.063 (497, 1,786) | 2,502 (1,169, 4,204) |
| Wheat | 26 (11, 46) | 15 (7, 27) | 41 (18, 73) | 654 (286, 1,129) | 388 (169, 673) | 1,042 (455, 1,802) |
| Cotton | 33 (15, 56) | 15 (7, 26) | 48 (22, 82) | 838 (403, 1,388) | 383 (178, 644) | 1,221 (581, 2,032) |
| **Total** | **177 (80, 304)** | **117 (54, 201)** | **294 (134, 505)** | **4,445 (2,064, 7,486)** | **2,923 (1,355, 4,933)** | **7,368 (3,419, 12,419)** |

* Note: 95 % CI for deaths were obtained from Abbafati et al. 2020 study only. Point estimates from EPA were assumed to be certain as 95% CI for $PM_{2.5}$ was not available in the data source.

**Figure 1.1**: Annual CVD and COPD deaths from crop-tillage emissions.




The estimated health economic cost of the deaths was about 12.9 billion USD per annum. Likewise, estimated annual DALYs was about 29,000 giving a health economic cost of about 2.9 billion USD (Tables 1.3-1.4). As expected, mortality attributable to soybean and corn-tillage emissions were highest in the mid-western corn-belt states, including Illinois (highest), Indiana (2$^{nd}$), Ohio (3$^{rd}$), and Iowa (4$^{th}$) (Table 1.5). Mortality attributable to wheat and cotton-tillage emissions was highest in the state of Texas.

As per the EPA's National Emissions Inventory Support Document (U.S. Environmental Protection Agency, 2021a), the difference in the primary $PM_{2.5}$ emissions arising from conventional tillage system versus conservation tillage system for a given crop is determined mainly by the difference in number of tillage passes between the two systems. Thus, we estimated that 283 annual deaths from CVD and 83 annual deaths from COPD attributable to conventional tillage can be averted upon shifting from conventional to conservation tillage practice (Table 1.6).

This is a total of about 360 annual deaths with the health economic value of the lives saved at about 3.6 billion USD.

**Table 1.5**: Total CVD and COPD deaths attributable to $PM_{2.5}$ from each crop-tillage combination by state (IT= Conventional tillage, RT= Conservation tillage).

| | **Soybean** | | **Corn** | | **Wheat** | | **Cotton** | |
|---|---|---|---|---|---|---|---|---|
| | **IT** | **RT** | **IT** | **RT** | **IT** | **RT** | **IT** | **RT** |
| Alabama | 0 | 0 | 1 | 0 | 0 | 1 | 4 | 4 |
| Arizona | 0 | 0 | 0 | 0 | 2 | 0 | 7 | 3 |
| Arkansas | 11 | 4 | 3 | 1 | 1 | 1 | 8 | 5 |
| California | 0 | 0 | 3 | 0 | 8 | 2 | 23 | 6 |
| Colorado | 0 | 0 | 1 | 0 | 2 | 2 | 0 | 0 |
| Connecticut | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Delaware | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 |
| Florida | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1 |
| Georgia | 0 | 0 | 1 | 0 | 1 | 0 | 11 | 7 |
| Idaho | 0 | 0 | 0 | 0 | 4 | 1 | 0 | 0 |
| Illinois | 49 | 37 | 54 | 41 | 6 | 5 | 0 | 0 |
| Indiana | 48 | 34 | 44 | 31 | 5 | 4 | 0 | 0 |
| Iowa | 16 | 20 | 22 | 27 | 0 | 0 | 0 | 0 |
| Kansas | 6 | 4 | 3 | 3 | 5 | 3 | 0 | 0 |
| Kentucky | 6 | 5 | 4 | 4 | 2 | 2 | 0 | 0 |
| Louisiana | 5 | 3 | 2 | 2 | 0 | 0 | 3 | 4 |
| Maine | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Maryland | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 |
| Massachusetts | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Michigan | 18 | 9 | 15 | 8 | 8 | 5 | 0 | 0 |
| Minnesota | 12 | 6 | 13 | 7 | 3 | 1 | 0 | 0 |
| Mississippi | 8 | 3 | 2 | 1 | 0 | 0 | 9 | 6 |
| Missouri | 9 | 7 | 4 | 4 | 2 | 2 | 2 | 2 |

**Table 1.5**: (cont'd)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Montana | 0 | 0 | 0 | 0 | 2 | 1 | 0 | 0 |
| Nebraska | 2 | 2 | 3 | 4 | 0 | 0 | 0 | 0 |
| Nevada | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| New Hampshire | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| New Jersey | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| New Mexico | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| New York | 3 | 1 | 5 | 2 | 3 | 2 | 0 | 0 |
| North Carolina | 7 | 2 | 4 | 1 | 3 | 1 | 5 | 3 |
| North Dakota | 2 | 1 | 1 | 0 | 2 | 1 | 0 | 0 |
| Ohio | 36 | 32 | 23 | 21 | 9 | 9 | 0 | 0 |
| Oklahoma | 2 | 1 | 1 | 0 | 14 | 5 | 4 | 1 |
| Oregon | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| Pennsylvania | 3 | 3 | 5 | 5 | 3 | 3 | 0 | 0 |
| Rhode Island | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| South Carolina | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 3 |
| South Dakota | 3 | 2 | 4 | 2 | 1 | 0 | 0 | 0 |
| Tennessee | 4 | 3 | 2 | 1 | 1 | 1 | 2 | 2 |
| Texas | 1 | 0 | 13 | 2 | 15 | 5 | 68 | 22 |
| Utah | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| Vermont | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Virginia | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| Washington | 0 | 0 | 0 | 0 | 5 | 4 | 0 | 0 |
| West Virginia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Wisconsin | 9 | 6 | 12 | 9 | 2 | 1 | 0 | 0 |
| Wyoming | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | **265** | **190** | **250** | **185** | **115** | **67** | **152** | **70** |

Note: Smaller values have been rounded down to zero. The total deaths add up to 1295 instead of 1,296 due to rounding.

**Table 1.6**: Deaths averted when shifting from conventional tillage to conservation tillage.

| | CVD deaths averted | | | | COPD deaths averted | | | |
|---|---|---|---|---|---|---|---|---|
| | **Soybean** | **Corn** | **Wheat** | **Cotton** | **Soybean** | **Corn** | **Wheat** | **Cotton** |
| Alabama | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Arizona | 0 | 0 | 1 | 2 | 0 | 0 | 0 | 1 |
| Arkansas | 4 | 1 | 0 | 2 | 1 | 0 | 0 | 1 |
| California | 0 | 1 | 3 | 7 | 0 | 0 | 1 | 2 |
| Colorado | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Connecticut | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Delaware | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Florida | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Georgia | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 1 |
| Idaho | 0 | 0 | 2 | 0 | 0 | 0 | 1 | 0 |
| Illinois | 19 | 21 | 2 | 0 | 6 | 6 | 0 | 0 |
| Indiana | 18 | 17 | 1 | 0 | 6 | 5 | 0 | 0 |
| Iowa | 6 | 9 | 0 | 0 | 2 | 3 | 0 | 0 |
| Kansas | 2 | 1 | 2 | 0 | 1 | 0 | 1 | 0 |
| Kentucky | 2 | 2 | 1 | 0 | 1 | 1 | 0 | 0 |
| Louisiana | 2 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| Maine | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Maryland | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Massachusetts | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Michigan | 7 | 6 | 3 | 0 | 2 | 2 | 1 | 0 |

**Table 1.6**: (cont'd)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Minnesota | 4 | 5 | 2 | 0 | 1 | 2 | 1 | 0 |
| Mississippi | 3 | 1 | 0 | 3 | 1 | 0 | 0 | 1 |
| Missouri | 3 | 2 | 1 | 1 | 1 | 1 | 0 | 0 |
| Montana | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Nebraska | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Nevada | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| New Hampshire | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| New Jersey | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| New Mexico | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| New York | 1 | 2 | 1 | 0 | 0 | 0 | 0 | 0 |
| North Carolina | 3 | 2 | 1 | 1 | 1 | 0 | 0 | 0 |
| North Dakota | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Ohio | 14 | 9 | 3 | 0 | 4 | 3 | 1 | 0 |
| Oklahoma | 1 | 0 | 4 | 1 | 0 | 0 | 1 | 0 |
| Oregon | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Pennsylvania | 1 | 2 | 1 | 0 | 0 | 1 | 0 | 0 |
| Rhode Island | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| South Carolina | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| South Dakota | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Tennessee | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| Texas | 1 | 5 | 5 | 20 | 0 | 1 | 1 | 5 |
| Utah | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 1.6**: (cont'd)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Vermont | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Virginia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Washington | 0 | 0 | 2 | 0 | 0 | 0 | 1 | 0 |
| West Virginia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Wisconsin | 3 | 5 | 1 | 0 | 1 | 1 | 0 | 0 |
| Wyoming | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Total** | **102** | **96** | **39** | **45** | **30** | **29** | **12** | **12** |

Note: Smaller values have been rounded down to zero.

## 1.4 Discussion

The total annual $PM_{2.5}$ emissions from all sources was about 5.24 million tons (U.S. Environmental Protection Agency, 2017). As the primary $PM_{2.5}$ emissions from the tillage of the four crops was 0.25 million tons, it comprised about 5 % of the total annual $PM_{2.5}$ emissions in the contiguous USA. Not surprisingly, the agriculture-intensive Midwestern states and Texas, the largest state in the contiguous USA with 74% of its total land devoted to agriculture (Hundl, 2021), had the highest public health burden due to tillage-related $PM_{2.5}$ emissions.

Estimated annual deaths due to CVD and COPD in the US in 2020 were about 697,000 (CDC, 2022) and 150,000 (CDC National Center for Health Sciences, 2022) respectively. Since 1,002 and 294 deaths due to CVD and COPD respectively were attributable to emissions from crop tillage, the deaths attributable to crop-tillage emissions comprise about 0.001% of the total CVD deaths and about 0.002% of the total COPD deaths. For context, a recent study finds that 17,900 annual deaths were attributable to US agriculture in which ammonia emission from livestock waste and fertilizer application was attributable to 12,400 deaths; and primary $PM_{2.5}$ from tillage, livestock dust, field burning and agricultural fuel use was attributable to 4,800 deaths (Domingo et al., 2021).

A recent paper by Behrer and Lobell 2022 used health point estimates from other studies to find that full adoption of the no-till practice in soybean fields in the US Corn Belt decreases $PM_{2.5}$ pollution leading to between 40-120 fewer deaths per year. For comparison, our study finds that 121 CVD deaths and 48 COPD deaths can be averted in the same region were there a shift from conventional to no-till practice in soybeans crop (we assume that no-tillage practice causes negligible emissions from soil disturbances). To place these mortality numbers in perspective, motor vehicle crashes caused about 43,000 deaths in 2022 (U.S. Department of Transportation's National Highway Traffic Safety Administration, 2023) and lung cancer from secondhand smoking causes 7,300 annual deaths (U.S. Department of Health and Human Services. Centers for Disease Control and Prevention, 2014).

We estimated that the shift from conventional to conservation tillage will have an expected monetary benefit of about 3.6 billion USD through a reduction in mortality assuming VSL at 10 million. For context, the market value of U.S. corn was about 92 billion USD in 2022/2023 (USDA National Agricultural Statistics Service, 2023). Similarly, we found that a shift from conventional to no-tillage practice averts about 783 annual deaths with a total monetary value of about 7.8 billion USD. For perspective, the study by Deryugina et al., 2019 found that average $PM_{2.5}$ level decreased by 4.9 $\mu g/m^3$, between 1999 and 2013 in the United States, resulting in an annual mortality reduction benefit of 24 billion USD among the elderly population aged 65 and above. In practice, while the value of adoption of conservation and no-tillage practices to reduce $PM_{2.5}$ pollution and consequently improve public health burden, must be recognized, a total shift to conservation or no-till practices is not realistic due the need for weed control and emergence of herbicide-tolerant weeds (Van Deynze et al., 2022) among other reasons.

To summarize, CVD and COPD mortality burden attributable to primary $PM_{2.5}$ emissions from crop-tillage made up only a small fraction of the total CVD and COPD mortality from all causes in the US. However, the mortality burden was not inconsequential and there is a substantial public health benefit of reducing conventional tillage. We understand that farmers' tillage choice will not depend on $PM_{2.5}$ emissions, but rather will likely depend on the comparative pecuniary and soil health benefits of each tillage choice. Nonetheless, promotion and adoption of reduced tillage and consequently reduced emissions maybe achieved through agricultural policies and on-farm measures in favor of conservation or no-tillage practices. We provide a discussion on some of these policies and measures in Chapter 2 of this work.

There are several limitations in this work. We did not have the estimated number of deaths and DALYs from CVD and COPD data at the county level. Thus, we imputed this data using state level prevalence data and county level rate of disease data. Although we do not anticipate the actual prevalence in the county level to be drastically different from our imputed estimates, there are possibilities of some differences. Furthermore, uncertainty estimates for $PM_{2.5}$ emissions were not available. Thus, uncertainty estimates for deaths and DALYs reported were derived with the assumption that the $PM_{2.5}$ estimates from crop-tillage combination are certain. In addition, several key factors that affect $PM_{2.5}$ emissions during tillage such as soil moisture, wind conditions, weather conditions, and emission travel across long distances could not be accounted in this study as we used the EPA's NEI 2017 methodology, which did not account for them. These factors are important as shown for instance in the Deryugina et al., 2019 study which found that local wind direction is a strong predictor of local $PM_{2.5}$ controlling for factors such as temperatures, precipitation, wind speed as well as other fixed effects variables. Due to the cross-sectional nature of the dataset, we could not model $PM_{2.5}$ pollution lags to investigate the health effects over time and we assumed that current emissions results in mortality outcomes within a year. Evidence suggests that acute $PM_{2.5}$ emissions has both an immediate and a long term effect adult mortality and health care costs; and we are also cognizant that mortality effects may vary and depend on factors such as sex and age of population, life expectancy differences in the population (i.e. age variation within the elderly population) and vulnerability to exposure (i.e. lung cancer status of population) (Deryugina et al., 2019; Franklin et al., 2007). It is also important to note that several factors such as individual's health, immunological states, prevalence of non-communicable diseases, and genetic factors maybe determinants of the severity of health effects from $PM_{2.5}$. Due to methodological limitations, these factors could not be considered in this study. Intra-county proximity to the $PM_{2.5}$ emission source was not accounted for when calculating disease burden due to methodological limitations.

## 1.5 Conclusion

In this chapter, we were able to estimate primary $PM_{2.5}$ emissions from crop-tillage combination of four common crops (corn, soybeans, wheat and cotton) and two different tillage type (conventional and conservation tillage) in the contiguous USA. We estimated that tillage related emissions made up about 5 % of the total emissions. We also estimated that the public health burden attributable to $PM_{2.5}$ emissions from crop-tillage in terms of mortality and DALYs from CVD and COPD was about 1,300 annual deaths and about 29,000 annual DALYs. Our estimates show that although the CVD and COPD mortality associated with crop-tillage emissions is a small fraction of the total mortality, the health economic costs were not insignificant, and valued at about 13 billion USD. We estimated that 283 annual deaths from CVD and 83 annual deaths from COPD attributable to conventional tillage can be averted upon shifting from conventional to conservation tillage practice. This is a total of 366 annual deaths with the health economic value of the lives saved at about 3.6 billion USD, thus highlighting the importance of moving from conventional tillage to conservation tillage practices not only for the purpose of good soil health, environmental benefits, but also for reducing mortality and health economic costs.

## **Chapter 2:** Optimal subsidy for conservation tillage adoption and its implementation

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### 2.1 Introduction

Agricultural production plays a key role in ensuring public health by providing healthy, safe, and nutritious food for people (Kanter et al., 2015; Wallinga, 2017). Agriculture is an essential sector of both local and national economies as it provides affordable food for increased demand, export commodities, rural employment and income as well as raw materials such as fiber and oil for the manufacturing sector (Johnston & Mellor, 1961; Pretty et al., 2001). However, agricultural activities use natural resources such as land and water and has the potential to create both negative and positive externalities that affect public health outside of the production-consumption interaction (Jongeneel et al., 2016; Tegtmeier & Duffy, 2004). Negative environmental externalities of agricultural activities often include soil degradation; greenhouse gas emissions; pesticide, herbicide and fertilizer run-off to nearby water bodies and land; and degradation of freshwater sources among others (Global Panel, 2020; Tegtmeier & Duffy, 2004). In addition, agriculture has negative health externalities such as damage to human health from air pollution, pesticide residue and disease agents in food, and overuse of anti-biotics among others (Pretty et al., 2001). In contrast, agricultural activities may have positive environmental externalities such as aesthetic value, water supply, nutrient fixation in soil, soil formation, biodiversity, flood control and carbon sequestration (Jongeneel et al., 2016; Lewis et al., 2008; Natali & Branca, 2020).

Over the past several decades, a growing awareness on the negative environmental externalities of agriculture has led to innovations and adoption of agricultural technologies such as conservation tillage, integrated pest management, nutrient testing, precision agriculture (Fuglie & Kascak, 2001). The role of agricultural technologies on reducing negative externalities related to environment, soil health, and ecosystem have often been discussed. In Chapter 1 of this work, we had discussed the effect of agricultural tillage on primary $PM_{2.5}$ emissions highlighting that conservation and no-tillage systems cause minimum soil disturbances and consequently minimum primary $PM_{2.5}$ emissions along with soil health and environmental benefits.

In the United States (US), early experiments on conservation tillage were carried out in the 1940s and 1950s, but this tillage system was not extensively used until 1970s and 1980s when a confluence of technological advances such as high yield varieties, tractor power, machinery design for conservation practices, and development of chemical herbicides such as atrazine and glyphosate occurred (Allmaras & Dowdy, 1985). Other factors such as lower fuel cost from conservation practices, public concern on soil erosion and land degradation, and government programs also played a role in conservation tillage adoption. In the United States and elsewhere, conservation tillage and no-tillage adoption increased in major field crops such as corn and soybeans between 1960s to 1990s (Fuglie & Kascak, 2001; Triplett & Dick, 2008; N. D. Uri, 1999). In 2017, about 80 million acres (28%) of the US farm land used conventional tillage, about 98 million acres (35%) used conservation tillage, and about 104.5 million acres (37%) used no-till practices (Zulauf & Brown, 2019). Table 2.1 gives information on the tillage practices used in four major crops- soybean, corn, wheat, and cotton- for different years in the United States.

The adoption and diffusion of conservation tillage system occurred rapidly after the advent of transgenic glyphosate tolerant (GT) crops in 1996 and use of glyphosate, a broad-spectrum herbicide which provided an effective and convenient post-emergent weed control. This shows a complementary relationship between GT crops and conservation tillage practices (Perry et al., 2016). However, due to the exclusive use of glyphosate and GT variety for common crops such as corn, soybeans, wheat, and cotton, there has been an emergence of glyphosate resistant weed species (Shaner & Beckie, 2014). This has led to the increase in use of other non-glyphosate herbicide which often have higher costs. Higher costs for herbicide control and resistance of multiple weeds to glyphosate has led to an unfortunate reduction of conservation tillage especially from late 2010s (Van Deynze et al., 2022).

**Table 2.1**: Tillage practices by crop in different years in the United States.

| **Crop** | **Year** | **Conventional tillage** | **Conservation tillage** | **No-till** |
|---|---|---|---|---|
| Soybean | 2012 | 30% | 30% | 40% |
| Corn | 2016 | 35% | 38% | 27% |
| Wheat | 2017 | 33% | 22% | 45% |
| Cotton | 2015 | 60% | 22% | 18% |

Source: Claassen R, Bowman M, McFadden J, Smith D, Wallander S. Tillage Intensity and Conservation Cropping in the United States EIB-197, U.S. Department of Agriculture, Economic Research Service, September 2018.; 2018. doi:10.22004/AG.ECON.277566

Generally agricultural technology adoption by farmers is dependent on profit maximization or utility maximization under given constraints such as land, labor, credit (Feder et al., 1985). At the farm level, the rate adoption of new technologies is dependent on factors such as credit access, information availability, farm type, farm size, farmer education and learning, risks and uncertainty, labor availability, soil quality and geography among others (Feder et al., 1985; Feder & Umali, 1993; Fuglie & Kascak, 2001). Likewise, adoption of a tillage practice is a choice dependent on the benefits and costs of each tillage type and mitigation of soil health risks. Factors that promote conservation tillage system often include positive attitude towards conservation tillage, adoption of other conservation practices, larger farm size, planting of row crops, presence of highly erodible land, information seeking, affiliation to agricultural organization and higher years of formal education among others (J. Lu et al., 2022). Farmers are aware of the soil health benefits of conservation tillage such as accumulation of organic carbon in the upper soil, better soil moisture, promotion of microbial and earthworm activity, improved soil stability, and reduced soil erosion runoff and losses (Busari et al., 2015; Tebrügge & Düring, 1999). The costs associated with conservation tillage usually involves higher costs for inputs such as fertilizer, herbicides, and pesticides.

Exogenous to these factors, benefits from government programs have played an important role in encouraging farmers to adopt conservation tillage practices. The "Conservation Compliance" is an example of a voluntary US government program where farmers are required to limit soil erosion on highly erodible land to get benefits such as price and income supports, disaster relief, loans, conservation payments, credit support and other benefits (Doering & Smith, 2012). Similarly, the Environmental Quality Incentives Program (EQIP) is a program introduced in 1996 farm bill that provides technical and financial assistance to farmers to address natural resource concerns and deliver environmental benefits such as reduced soil erosion and improved air quality through direct particulate matter emissions reduction (USDA Natural Resources Conservation Service, 2023).

Generally, government programs have been implemented recognizing the positive environmental benefits associated with conservation tillage such as the reduction in soil erosion, improvement in water quality and lower carbon emissions (N. Uri et al., 1998). However, the same cannot be said of promoting conservation tillage in the context of reducing negative health outcomes. The role of conservation tillage adoption on public health through reduced pollution has garnered less attention. The Behrer and Lobell, 2022 study, which is one of the few studies investigating no-till adoption and reduced air pollution health effects, points out that the reduction of mortality through decreased $PM_{2.5}$ emissions from the adoption of reduced tillage is not well understood (Behrer & Lobell, 2022).

In chapter 1 of this work, we discussed how agricultural practices lead to $PM_{2.5}$ emissions that is related to adverse public health outcomes and health economic costs. We also estimated the annual mortality and DALYs from cardiovascular diseases (CVD) and chronic obstructive pulmonary diseases (COPD) attributable to tillage-related emissions. In this chapter, we focus on developing a conceptual framework for calculating the optimal subsidy amount which internalizes the positive health benefits of conservation tillage adoption in terms of reduction in deaths due to primary $PM_{2.5}$ emissions. We then use this conceptual framework and the mortality decrease and emission reduction values from chapter 1 to estimate the optimal subsidy amount for conservation tillage adoption for soybean crops in Iowa. Later, we use values from a prior study by Perry et al., 2016 to find the implications of such a subsidy in terms of probability of conservation tillage adoption. Finally, we discuss agricultural policies and on-farm measures which may help reduce $PM_{2.5}$ emissions.

## 2.2 Conceptual framework for calculating an optimal subsidy

We developed a conceptual framework to calculate the optimal subsidy for conservation tillage that addresses external health effects arising from the practice. For this conceptual framework, we ignore all other externalities that attend the tillage practice choice such as greenhouse gas emissions through soil disturbance, machinery use and fossil fuel consumption.

A unit of land with a crop can be allocated to either conventional tillage or conservation tillage (Figure 2.1). With $\theta \in [0,1]$ as an index for conservation tillage suitability with distribution $G(\theta)$ and density function $g(\theta)$, we assume a profit-determined cutoff value $\theta^*$ above which land acres are more profitably allocated to conservation tillage instead of conventional tillage. We assume that there is no option to sow to another crop or use a third technology such as no-till. Let $\pi^h(\theta)$ and $\pi^l(\theta)$ be the respective per acre profits for conventional tillage and conservation tillage and let $\theta$ be ordered such that $J(\theta) \equiv \pi^l(\theta) - \pi^h(\theta)$ is increasing in $\theta$. The value $\theta^*(s)$ is defined as the conservation tillage suitability value satisfying the condition $\pi^l(\theta)|_{\theta=\theta^*(s)} + s = \pi^h(\theta)|_{\theta=\theta^*(s)}$, i.e., the value at which land allocated to maximize profit is at the margin between using the two tillage technologies when a per acre Pigouvian subsidy $s$ is provided to those who use conservation tillage rather than conventional tillage. Aggregated profit is then given by

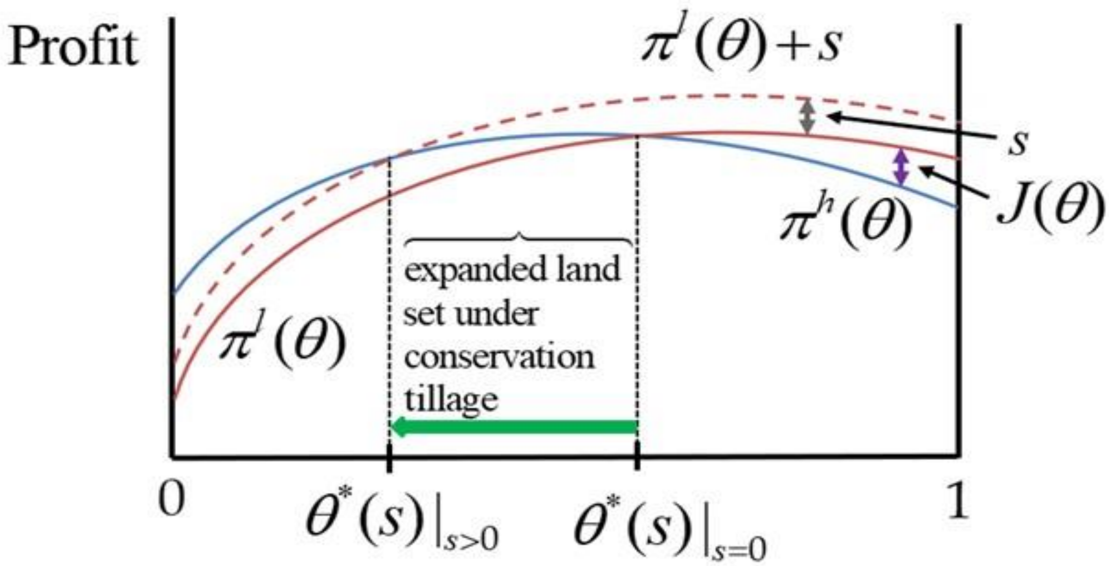
$$(8) \qquad V(\theta^*(s); s) = \int_0^{\theta^*(s)} \pi^h(\theta) dG(\theta) + \int_{\theta^*(s)}^1 [\pi^l(\theta) + s] dG(\theta)$$

Figure 2.1 characterizes possible specifications for profits and alternative cutoffs as the size of practice-specific subsidy changes. As we seek to understand implications of moving from conventional to conservation tillage, the policy considered is the optimal US dollar amount per-acre subsidy provided only to the land under the conservation tillage practice.

To establish a metric for social welfare, we represent health damage under conventional tillage as $Nvp^h$ where $N$ is the affected human population, $v$ is the value of a statistical life (or deaths averted in our case) expressed in USD for a ton of $PM_{2.5}$ emissions per acre per pass and $p^h$ is the number of tillage passes under conventional tillage. The acreage share at issue is the land fraction satisfying $\pi^l(\theta)|_{\theta=\theta^*(s)} + \; s \leq \pi^h(\theta)|_{\theta=\theta^*(s)}$, i.e., $G(\theta^*(s))$ where we arbitrarily assign equal profit acres to the conventional tillage. Similarly, let health damage under conservation tillage be $Nvp^l$ with relevant acreage $1 - G(\theta^*(s))$. Thus, social welfare may be represented by aggregated profit from equation (8) minus the health damage under both tillage practices. This is given by

(9) $$W(s) = V(\theta^*(s); s) - [1 - G(\theta^*(s))]s - Nvp^h G(\theta^*(s)) - Nvp^l[1 - G(\theta^*(s))]$$

**Figure 2.1**: This figure shows the estimations of effects of a practice-specific subsidy on land allocated to conservation tillage vs. conventional tillage. Here, θ ∈ [0,1] is an index for conservation tillage suitability with distribution G(θ) and density function g(θ). θ* is the profit determined cutoff value above which land acres are allocated to conservation tillage instead of conservation tillage. $\pi^h$ (θ) and $\pi^l$ (θ) are the respective per acre profits for conventional tillage and conservation tillage and s is the subsidy amount.



Our goal is to identify the per acre subsidy that maximizes social welfare by internalizing the effect of tillage on $PM_{2.5}$ pollution. Note the following simplifying calculation, due to the fundamental theorem of calculus (Leibniz' integral rule) and the definition of $\theta^*(s)$:

$$\frac{dV(\theta^*(s);s)}{ds} = \pi^h(\theta^*(s))g(\theta^*(s))\frac{d\theta^*(s)}{ds} - [\pi^l(\theta^*(s)) + s]g(\theta^*(s))\frac{d\theta^*(s)}{ds} + \int_{\theta^*(s)}^{1} dG(\theta)$$

$$= \overbrace{[\pi^h(\theta^*(s)) - [\pi^l(\theta^*(s)) + s]}^{=\,0\text{ by definition}}\, g(\theta^*(s))\frac{d\theta^*(s)}{ds} + 1 - G(\theta^*(s))$$

(10) $$= 1 - G(\theta^*(s)).$$

We then applied the envelope theorem as the land allocation decision involves choice optimization. When evaluating at the optimal subsidy point $s$*, the per acre profit from conventional tillage is equal to the sum of per acre profit from conservation tillage and the subsidy amount. The optimal subsidy $s$* then satisfies

$$\frac{dW(s)}{ds} = \frac{dV(\theta^*;s)}{ds} - [1 - G(\theta^*(s))] + sg(\theta^*(s))\frac{d\theta^*(s)}{ds} - Nvp^h g(\theta^*(s))\frac{d\theta^*(s)}{ds}$$
$$+ Nvp^l g(\theta^*(s))\frac{d\theta^*(s)}{ds}$$

$$= [1 - G(\theta^*(s))] - [1 - G(\theta^*(s))] + [s - Nvp^h + Nvp^l]g(\theta^*(s))\frac{d\theta^*(s)}{ds}$$

(11) $$= [s - Nvp^h + Nvp^l]g(\theta^*(s))\frac{d\theta^*(s)}{ds} = 0.$$

In the above, the subsidy cancels out (first two terms, penultimate line) because it is simply a transfer from the government to the farmer. As $g(\theta^*(s))d\theta^*(s)/ds$ is likely other than zero, the optimal subsidy per acre is, therefore, the intuitive value

(12) $$s^* = Nv(p^h - p^l)$$

whereby the marginal decrease (and in this case the average decrease too because disease burden scales linearly with number of tillage passes) in value of statistical lives lost is given as a subsidy to incentivize the tillage practice change. The optimal subsidy can be readily estimated, given that reasonable estimates of all four parameters are available.

## 2.3 Results

### 2.3.1 Estimation of the optimal subsidy for conservation tillage adoption

Based on the conceptual framework elaborated earlier, we estimated the optimal Pigouvian subsidy for soybean conservation tillage adoption in Iowa. For soybean, a change in practice from conventional to conservation tillage involves a change from two agricultural tillage passes to one pass (U.S. Environmental Protection Agency, 2021a). In Iowa, about 5 million acres of soybeans were planted under conventional tillage in 2017 (USDA, 2019). From our calculations we know that a shift from conventional to conservation tillage for soybean crop in Iowa reduces $PM_{2.5}$ emissions by a total of 2009.4 tons as one pass generates 0.00041 tons of emissions per acre. The effect of a reduction of 2009.4 tons of $PM_{2.5}$ emissions was averting a total of 8 annual deaths from both CVD and COPD, giving a value of 0.0039 deaths per ton of emissions. A standard estimate for the value of a statistical life (VSL) is 10 million USD (Kniesner & Viscusi, 2019). Thus, the value of *v* in USD for a ton of $PM_{2.5}$ emissions for an acre per pass is equal to the VSL times the $PM_{2.5}$ emissions for an acre per pass (i.e. 10 million USD times 0.00041 tons of $PM_{2.5}$ emissions for an acre per pass). Hence, we calculated the optimal per acre subsidy for soybean under conservation tillage, $s*$, by using multiplying these parameters in equation (12) as follows

$$s^* = Nv(p^h - p^l)$$

$$= 0.00398 \frac{deaths\ averted}{ton\ of\ PM_{2.5}\ emissions} \times 4100\ \frac{(USD)\ (ton\ of PM_{2.5}\ emissions\ for\ an\ acre/pass)}{deaths\ averted}$$

$$\times (2-1) \frac{pass}{for\ changing\ from\ conventional\ to\ conservation\ tillage}$$

$$= 16.3\ \text{USD}\ for\ an\ acre\ for\ changing\ from\ conventional\ to\ conservation\ tillage$$

Thus, we calculated that the optimal per acre subsidy $s*$ for soybean planting considering the reduction only in CVD and COPD deaths is 16.3 USD per acre for a change from conventional to conservation tillage.

### 2.3.2 Implications of the optimal subsidy on conservation tillage adoption

To infer implications for practical adoption of such a Pigouvian subsidy, we appealed to the analysis in the Perry et al. (2016) study where conventional tillage or lower tillage levels were considered for soybean in a structural discrete choice model and estimated jointly with the glyphosate tolerance seed choice. To summarize, fuel price was among the explanatory variables included when modeling the choice between conventional tillage or conservation tillage of some level. Perry et. al reasoned that lower fuel price will increase the economic competitiveness of conservation tillage because the most distinctive difference between the alternative tillage systems is the change in number of tillage passes, $-(p^h - p^l)$, and so the change in fuel expenditure. They used data at the sub-farm level of disaggregation for the contiguous United States over the 1998-2011 time interval. Perry et al. (in table 3 of their study) estimated

(13) $dProb[CT]/dP_{Fuel} = 0.0069$

where $\mathrm{Prob}[CT]$ represents the probability that a given soybean planting is under conservation tillage, and $P_{\mathrm{Fuel}}$ is a USDA-NASS fuel price index with 1998-2011 time interval average of 49.96.

We used equation (13) to calculate the change in probability of conservation tillage in terms of a change in a USD per acre subsidy i.e., $d\mathrm{Prob}[CT]/\,ds$. First, we converted equation (13) into actual fuel prices instead of a fuel price index. Since the average diesel fuel price was 2.22 USD per gallon in the same period (U.S. Energy Information Administration, accessed September 2022), a change of 1 unit of fuel price index is equivalent to a change of 0.044 USD per gallon in actual diesel fuel price. Thus, the change in probability that a given soybean planting is under conservation tillage for a USD per gallon change in diesel fuel price can be written as

(14) $dProb[CT]/dP_{Actual\ fuel\ \text{price}} = 0.0069/0.044 = 0.1568$

where, $\text{Prob}[CT]$ is the probability of soybean planting under conservation tillage and $P_{Actual\ fuel\ \text{price}}$ is the price of diesel fuel in USD per gallon.

We then rewrote this probability in terms of cost of diesel fuel per acre to express the probability in terms of "USD per acre", which is the same unit as the optimal per acre Pigouvian subsidy. The average quantity of diesel required for conventional tillage and for no tillage practice are 6.05 and 1.89 gallons per acre respectively (Conservation Effects Assessment Project. Natural Resources Conservation Service. USDA, 2016). Assuming that i) the fuel quantity required for the no tillage practice is the baseline fuel quantity required regardless of the tillage practice used in soybean, and ii) the major difference between conservation and conventional tillage is 1 tillage pass, we calculated the fuel quantity required per pass per acre to be 2.08 gallons. Using the fact that the cost of fuel per acre is equal to the price of fuel times the quantity of fuel per acre, we re-wrote equation (14) in terms of cost of fuel as

(15) $Q_{ActualFuel} \times d\text{Prob}[CT]/dC_{Actual\ Fuel} = 0.1568$

where, $C_{Actual\ Fuel}$ is the cost of diesel fuel per acre in USD and $Q_{ActualFuel}$ is the quantity of fuel per acre in gallons. The cost of diesel fuel per acre is equivalent to a Pigouvian tax or subsidy per acre. For instance, an increase in diesel fuel cost by 1 USD is comparable to a 1 USD tax levied on conventional tillage (due to the need of an additional tillage pass and more fuel required) or a USD subsidy provided for conservation tillage (due to the avoidance of one tillage pass and saving on fuel). Thus, we rewrote equation (15) as

(16) $d\text{Prob}[CT]/\ dC_{Actual\ Fuel} = d\text{Prob}[CT]/\ ds = 0.1568/Q_{Actual\ Fuel} = 0.0754$

where, $d\text{Prob}[CT]/\ ds$ represents the probability of conservation tillage practice for a USD change in subsidy per acre amount.

Finally, we calculated the total acreage changes for soybean under the optimal per acre Pigouvian subsidy, $s$*, by taking the product of the change in probability of conservation tillage for a change in one USD subsidy, the optimal per acre subsidy and the total acres of soybean planted under both conventional and conservation tillage practice. This is given by

$\text{dProb[CT]/ds} \times \text{s} * \times$ (Total acres of soybean under both tillage practice)

$= 0.0754 \times 16.3 \times 10{,}500{,}000$ acres

$= 12{,}904{,}710$ acres (or approximately 12.9 million acres)

Thus, in theory approximately 12.9 million acres of soybean planted under conventional tillage practice will shift to conservation tillage practice in Iowa, if 16.3 USD per acre subsidy is provided.

## 2.4 Discussion

We calculated that the optimal per acre Pigouvian subsidy amount was 16.3 USD for a shift from conventional to conservation tillage while considering only the positive health benefits from air pollution reduction. To put that number in perspective, Gramig and Widmar (2018) estimate that the willingness to accept (WTA) payment among corn and soybean farmers in Indiana who have not previously adopted any form of no-till or conservation till was USD 14.2 per acre to undertake no-till instead of conservation tillage and USD 39.4 to undertake no-till instead of conventional tillage. For prior adopters of no-till, the WTA payment to adopt no-till were much lower. Also for perspective, the cash rent for soybean cropland in Iowa in 2022 was about 256 USD per acre (Plastina & Johanns, 2022). Using Perry et. al., we found that for every 1 USD per acre subsidy, the probability of conservation tillage adoption for soybean increases by

0.0754 (or 7.54%). Hence, at the optimal per acre subsidy of 16.3 USD, we found that theoretically 12.9 million acres of soybean planted under conventional tillage system will shift to conservation tillage system in Iowa. In reality, only approximately 5 million acres of soybean are planted under conventional tillage in Iowa and so we project that most of these acres would convert to conservation till if the subsidy is provided. However, the Perry et. al. study estimate is only valid for responses within the range of historical data and there will always be a need for conventional tillage on land with, for example, recalcitrant weed issues.

We recognize the challenges that would arise in the implementation of such a subsidy as there will be the issues of measuring and verifying tillage practice in the agricultural fields. At present under the 1985 US farm bill, the "conservation compliance program" practices includes conservation tillage practices for highly erodible soil; and voluntary compliance to conservation practices qualifies the farmers for federal farm payment, cost-sharing and loan programs (Doering & Smith, 2012). While some farmers are likely to practice reduced tillage on part or all of their farm land regardless of the incentives, evidence suggests that some farmers are unlikely to comply with conservation practices due to incentives from higher crop prices and poor monitoring and enforcement of conservation practices at the farm level. A 2020 study assessed conservation compliance in corn in the US corn belt region after the passage of the 2007 energy bill containing an ethanol mandate which led to an increase the price of corn in the subsequent years (Holland et al., 2020). This study found an increase of acreage of continuous corn planting, a proxy indicator of conservation program non-compliance, in highly erodible soil area and also found a strong correlation between corn price and continuous corn acres in the 2006-2019 time period. Similarly, a study by Claassen et al., 2017 estimated that even in a "medium" crop price scenario, conservation compliance benefits are low compared to compliance cost in 28 percent (i.e. 27

million acres) of highly erodible land under conservation compliance. In addition, a 2016 audit report pointed out monitoring and enforcement issues in conservation practices such as the National Resources Conservation Service (NRCS) staff monitoring only certain areas of a farm land, inconsistencies in compliance standards between different states for gully erosion in highly erodible lands, and limited sampling of highly erodible land (USDA Office of Inspector General, 2016). Farmers have been cited for violations for not complying with the conservation terms while participating in the conservation program and often the payment size, costs, and enforcement of the policy are the economic determinants of such noncompliance (Giannakas & Kaplan, 2005). Despite of the compliance and monitoring issues, a Pigouvian subsidy for conservation tillage may be a policy tool which incentivizes farmers to adopt conservation tillage practices, providing the incidental benefit of reducing $PM_{2.5}$ pollution.

Another policy tool for reducing agricultural $PM_{2.5}$ pollution may be the implementation of carbon sequestration and greenhouse gas (GHGs) policies. Tillage is a major source of GHG emissions into the atmosphere (Busari et al., 2015). Carbon credit and payment programs, whether voluntary or compulsory, may recognize as credits for payment the GHGs avoided because of conservation tillage practices. But credits made not being truly "additional" i.e. conservation practices adopted without payment and permanence of carbon sequestration are issues that hinder growth in credit payments to guide agricultural practices toward lower emissions (Wongpiyabovorn et al., 2022). As agriculture contributed about 10% of US GHG emissions in 2020 (U.S. Environmental Protection Agency, 2022) , stringent GHG emissions policies are likely to involve agriculture and yield $PM_{2.5}$ emissions reduction as an incidental benefit.

At the farm level, planting cover crop is a crop management strategy that can reduce water and wind related soil erosion and consequently reduce $PM_{2.5}$ emissions. Such crops are generally sown during seasons or years when a cash crop is not grown. The cover crop practice is costly because it requires direct on-farm expenses for seed, equipment, and potentially other agricultural inputs (Snapp et al., 2005) and often reduce yield in primary crops such as maize and soybeans (Deines et al., 2023). Nonetheless, this practice provides many important benefits internal to the farm such as improved soil health attributes and reduction of soil erosion through cover protection (Plastina et al., 2020). Government agencies in the US have been active in promoting cover crops through free technical assistance and the Environmental Quality Incentives Payment (EQIP) program first established in the 1996 Farm bill. More recently, cover crop payments have been linked with federal crop insurance contract offerings by way of premium reductions (Hoffman, 2022). As cover crops can also feature in carbon sequestration strategies, any endeavors to monetize carbon sequestration may promote cover crops and consequently reduce $PM_{2.5}$ emissions as an incidental benefit.

Farmers may also reduce wind related soil erosion by windbreaks, the agroforestry practice involving linear plantings of trees and shrubs, in order to control for wind speed; and consequently dust emissions (Smith et al., 2021). However, windbreaks were found to be less effective or have no impacts in $PM_{2.5}$ reduction compared to a substantial reduction in $PM_{10}$ emissions possibly due to lower settling velocity of $PM_{2.5}$ particles in comparison to the larger $PM_{10}$ particles (Chang et al., 2019, 2021). Nonetheless, the indirect economic benefit of soil erosion control via windbreaks may incentivize farmers to use this practice.

Inputs such as herbicides are also important in adoption of conservation tillage system. Weed control is an important consideration while making tillage choices and effective weed control is often the most important benefit from conventional tillage. Conservation tillage became viable only with the availability of inexpensive and effective herbicides such as dicamba and glyphosate for effective weed control. Advances in weed management technologies have also played a major role in the adoption of conservation tillage. Chief among these since the mid-1990s in the US has been the availability of transgenic herbicide tolerant soybean, corn, and cotton crops; where the crop can be sprayed over to kill all weeds, but the crop plants themselves would survive (Perry et al., 2016). However, in recent years, tolerance among the targeted weeds to the main herbicide used, glyphosate, has rendered the spray-over approach for weed control less effective, resulting in a reversion to conventional tillage (Van Deynze et al., 2022).

The multi-decade dominance of glyphosate use for weed control has provided limited incentives for both private or public sector innovators to inquire into alternative weed control approaches (Shaner & Beckie, 2014). Dicamba is an alternative weed control herbicide and soybean and cotton crops tolerant to the chemical have become popular since the emergence of weed resistance to glyphosate (Wechsler et al., 2019). Thus, an approach to reduce tillage related $PM_{2.5}$ pollution can be the development and promotion of alternative herbicides such as Dicamba. Of equal importance is to protect the utility of herbicides in weed control and reduce herbicide tolerance in weeds by implementing sustainable practices such as smart herbicide mixtures, herbicides rotations, and integrated weed management program (Heap & Duke, 2018). Ensuring the viability of herbicides in weed control will help sustain conservation tillage practices and consequently limit $PM_{2.5}$ emissions as an incidental benefit.

Beyond the farm, protecting the viability of glyphosate tolerant seeds may help sustain conservation tillage practices. Although this trait is a private good marketed as an premium-garnering feature of commercial seed, it is unclear whether seed companies are protecting the asset to maximize the trait's market value or value to the public good in reducing usage of more toxic alternative herbicides (Ye et al., 2021), in reducing greenhouse gas emissions via decreased tilling

(C. Lu et al., 2022), or in reducing $PM_{2.5}$ emissions. For comparison, concerned about excessive plantings of transgenic Bt seed traits that would ultimately lead to insect resistance to Bt toxins and consequently to greater use of insecticides, the U.S. Environmental Protection Agency required biotech seed industries to enact insect resistance management strategies that Bt crop growers must follow to slow the spread of resistance (Morel et al., 2002; U.S. Environmental Protection Agency, 2001). No similar plan has been enacted for glyphosate tolerant crop planting.

There are some limitations associated with our work. As discussed previously when developing the conceptual model for the optimal subsidy, we ignored other externalities of tillage practice that may affect human health such as green-house gas emissions through soil disturbance and fossil fuel consumption and emissions. For the optimal subsidy calculation, we assumed that the mortality reduction benefits from the tillage practice change would be realized within one year.

## 2.5 Conclusion

The use of agricultural technology has the potential to mitigate various negative externalities related to environment and health. The adoption of conservation tillage system in place of conventional tillage has the environmental benefit in terms of reducing soil erosion and promoting soil health, but the public health benefits are less understood. We discussed that government programs provide incentives for conservation practices considering the soil health and environmental benefits; however, they do not consider the public health benefits of conservation tillage through reduction in $PM_{2.5}$ emission. In this chapter, we developed a conceptual framework for calculating the optimal subsidy that internalizes the positive health benefits of reduced mortality from lower $PM_{2.5}$ emissions when shifting from conventional tillage to conservation tillage practice. We then used this conceptual framework for calculating the optimal subsidy for shifting from conventional to conservation practice in soybean crops in the state of Iowa. We found that the optimal subsidy amount to be 16.3 USD per acre for changing from conventional tillage practice to conservation tillage. We also calculated that theoretically almost all soybean crop planted under conventional tillage in Iowa (currently at about 5 million acres) would shift to conservation tillage if the optimal subsidy is provided. Finally we also discussed agricultural policies such as subsidies, carbon capture credits and in-farm measures such as planting of cover crops, use of windbreaks, use of alternative herbicides, protection of the utility of herbicides and protection of glyphosate tolerant trait that may be beneficial in reducing tillage related $PM_{2.5}$ emissions and consequently reducing the public health burden associated with a key agricultural practice.

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