Title
Economic and Climatic Determinants of Farmer Suicide in the United States

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Economic and Climatic Determinants of Farmer Suicide in the United States

By

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Abstract

Farming has an elevated rate of suicide in the U.S. and elsewhere, which draws attention to the mental well-being of farmers and other agricultural workers. There is a rich empirical and conceptual literature exploring the reasons behind the high rate of farmer suicide. Yet little rigorous study addresses the determinants of farmer suicide in the U.S. This study explores a number of hypotheses as to causal factors explaining the high farmer suicide rate, including weather factors (e.g., extreme temperatures, variable precipitation) and economic factors such as price and income volatility.

A theoretical model is developed linking the weather and economic factors to a farmer's suicide decision. A farmer chooses between work effort and leisure, a level of consumption, levels of production inputs, and the amount of savings to maximize her utility given her budget constraint and time endowment. In a static model, a bad weather shock can have a "snowballing" effect that reduces farm income and also reduces utility from leisure and health through the work-leisure trade-off. Severe adverse weather outcomes can possibly diminish a farmer's utility and cause a spontaneous decision to commit suicide in extreme cases. Based on the model, we hypothesize that the marginal effect of harmful weather on farmer suicide is positive. Successive realization of bad weather and chronic poor economic conditions are positively associated with farmer suicide.

We combine the CDC nonpublic vital statistics, PRISM daily weather data, and the USDA National Agricultural Statistics Service data as a county-year panel to estimate the marginal effects of weather and economic factors on farmer suicides. Empirical analysis, based upon a Poisson regression model with agricultural district fixed effects, shows extreme heat is positively associated with farmer suicides. There is no clear

evidence of the effect of precipitation on farmer suicide in counties without irrigation. Chronic, not idiosyncratic, poor economic conditions induce farmer suicide. The results are robust to alternative specifications including or excluding year fixed effects.

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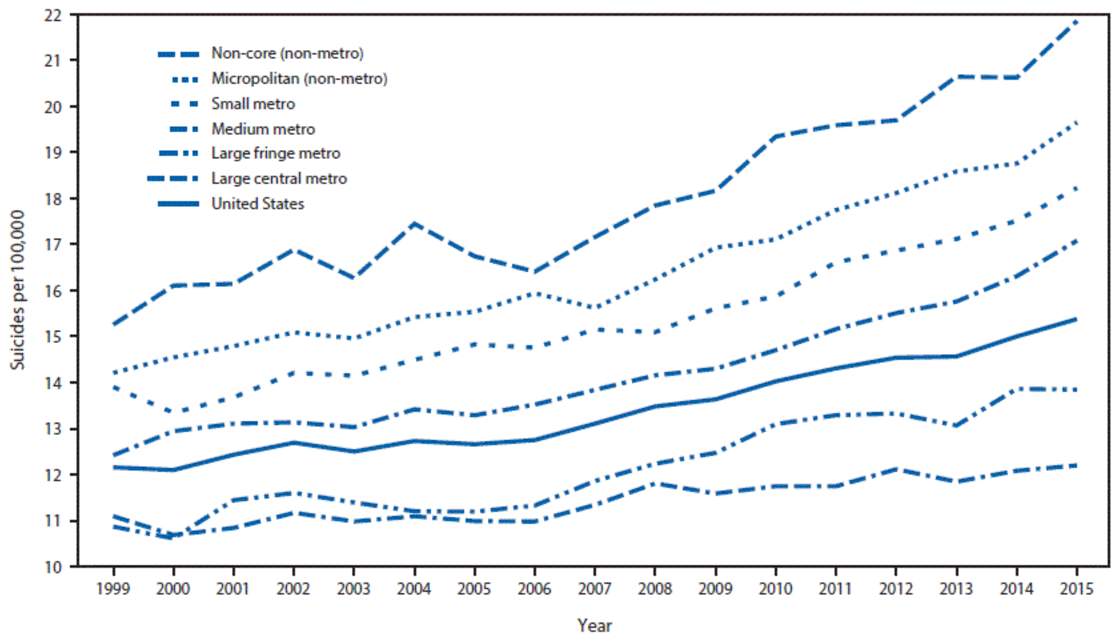
1 Introduction

Why do farmers commit suicide? The question merits attention, especially because farming has an elevated rate of suicide, in the U.S. and elsewhere. A report published by the Centers for Disease Control and Prevention Morbidity and Mortality Weekly Report indicates that suicide rates among male working age (persons aged 16-64 years) farmers, ranchers and other agricultural managers, as a subgroup of the managers major group, were the highest (44.9 per 100,000 population) of any occupational group in 2012 and the fourth highest (32.2 per 100,000 population) in 2015 in the U.S. For non-management agricultural workers, the suicide rates were 20.4 and 17.3 per 100,000 population in 2012 and 2015, respectively (Peterson et al., 2018).[1] These figures, however, could underestimate the real suicide rate in agriculture, as the data collected from 17 states excludes several major agricultural states, including the top 8 agricultural producing states in terms of cash receipts: California, Iowa, Texas, Nebraska, Minnesota, Illinois, Kansas and Indiana (USDA ERS, 2017).

Indeed, another CDC report highlights higher rates of suicide, and a significant rate of increase in areas with lower levels of urbanization, and demonstrates a growing disparity between rates in less urban and more urban areas of the United States (Kegler et al., 2017). The suicide rate among farmers, ranchers, and farm managers is even higher than the rate among the urbanization group with the highest suicide rate (about 22 per 100,000) in figure 1, which reveals that there must be something unique about farmers and farm managers that makes them so vulnerable to suicide. In addition, the suicide rates rising over time reminds us that it is time to study suicide as it becomes an increasingly important phenomenon.

[1] The report uses 2012 and 2015 National Violent Death Reporting System data from 17 states, including Alaska, Colorado, Georgia, Kentucky, Maryland, Massachusetts, New Jersey, New Mexico, North Carolina, Ohio, Oklahoma, Oregon, Rhode Island, South Carolina, Utah, Virginia, and Wisconsin.

Figure 1: Suicide rates by level of county urbanization, US, 1999-2015



These facts draw attention to the mental well-being of agricultural workers, especially agricultural managers. Yet people have almost no understanding of the factors that cause farmers to commit suicide. Ringgenberg et al. (2018) point out that farm operators and farm workers are significantly understudied in the area of violent workplace fatalities, yet studies consistently show that farmers are at increased risk for violent death, in particular suicide.

Factors that may influence farmer suicides include farm income, which has been dropping steadily since 2013. Agricultural producers usually have little market power relative to their downstream trading partners. Farmers may feel powerless to improve their livelihoods in these cases. The variability of agricultural incomes, risks associated with farming, and exposure of farmers to toxic chemicals are additional possible explanatory factors for the increased risk of violent death for farmers.

Climate change may also be a factor influencing the suicide rate among farmers. Recently published studies suggest that climate change may be related to suicides among the general population (Burke et al., 2018), but no evidence exists for farmers, who are a population group most likely to be impacted adversely by climate change. Relative to most other occupations, farmers work outdoors and are exposed to extreme weather conditions. Further, weather-induced crop failures due to climate change depress farm income and increase its variability, deepen farmers' debt burden, and diminish hope for future improvements, causing stress and, potentially, suicide.

The primary objective of this study is to explore the effects of climatic factors (e.g., extreme temperatures, variable precipitation) and economic factors on agricultural workers' suicide rates, especially on farmer suicide. Although a decision to commit suicide can be based on many factors not related to economic or climate/weather factors, our goal is to determine the extent to which these factors do play a causal role in farmer suicides. Better understanding of the factors contributing to farmer suicides could greatly improve the effectiveness of suicide prevention. It could also enrich our understanding of the foreseeable impacts of future climatic change.

2 Literature Review

An abundant literature studies the reasons for farmer suicide around the world. This section starts by reviewing psychology studies that explore factors that induce suicide in general, including the development of the research on suicide. Then, a qualitative analysis is made to suit the factors of suicide to farmers' situation. Next, I focus on empirical analyses that provide quantitative evidence to show the relationship between climate change and suicide in the general population. Then, farmer suicide situations in different countries are introduced. Some studies develop speculations to explain the high farmer suicide rates. Others demonstrate empirical evidence of causal factors relating to farmer suicide.

2.1 Psychology and sociology studies of suicide

> If the study of suicide had its own era it would divide into two ages, before and after that book ... Le Suicide ... which, more than any other, established its subject as a specialization.
>
> *Alexander Murray*

Before the seventeenth century, scholars believed that suicide is a result of psychological illness. There were even concerns about the contagion of suicide, or what is now often called copy-cat suicide. Peoples' understanding of the phenomenon was based on biological or personal factors. This began to change in 1987 with the publication of Emile Durkheim's classic book, *Suicide: A Study in Sociology*. The predominant focus of suicide research since the twentieth century was on the importance of inter-relationship with society and the psycho-social factors, influenced by the work of Durkheim.

The following section briefly introduces the studies on suicide before Durkheim and then reviews Durkheim's famous study of suicide. Then psychological and sociological studies on suicide post Durkheim are summarized.

2.1.1 General conclusions

In 1637, the first English publication on suicide, written by John Sym, pointed out from a theological point of view that suicide must be prevented by discovery and removal of the motives and causes, "as diseases are cured by removing the causes, rather than of their symptoms" (Sym & MacDonald, 2014). In the eighteenth century, people believed that suicide was a result of psychotic illness. Moore, one of the first to comment on possible genetic factors related to suicide, stated that suicide is hereditary (Moore, 1790).

In the nineteenth century, although people still deemed that suicide was a melancholic illness, which is possibly innate or hereditary, some scholars questioned the distinctions of sanity and insanity when explaining the cause of suicide. For example, Burrows (1828) argued that suicide is "sometimes perpetrated by a sane mind" and stated that "mental alienation" and "drunkenness and dissipation" were the two most common causes of suicide. Other postulated causes were debt, gambling, disappointed love, and the desire to avoid legal pursuit, nostalgia, and disgust with marriage.

Other than challenging the hereditary predisposition to suicide, there were also studies before Durkheim that utilized statistical analysis in conducting research into suicide, such as the association of age and education with suicide rates in different countries (Goldney et al., 2008).

Rejecting most of the accepted theories of suicide, Durkheim published his classical study of suicide, which demonstrated that neither psycho-pathic factors nor heredity nor other personal factors sufficiently motivate suicide. He claimed that suicide was not an individual act nor personal action, but, rather, primarily a social phenomenon in terms of the "breakdown of the vital bond of life." He also dismissed the predominant psychological theory of suicide as being a result of a pathological state of mind.

Relating the theory of suicide to his study of labor, he emphasized that the force which determines suicide is not psychological but social. He analyzed variations in suicide rate at a macro level, treating suicide as a society-scale phenomenon.

Durkheim's theory of suicide is the result of social disorganization or lack of social integration. He classified four types of suicide based on different types of relationships between the suicide actor and her society, focusing on the condition of group life, which comprise Egoistic, Altruistic, Anomic, and Fatalistic. Figure 2 shows the four types of suicide with social regulation on the x-axis, and social integration on the y-axis:

- **Egoistic suicide** corresponds to a low level of social integration. When a person becomes socially isolated (not well integrated into a social group) or feels that she has no place in society, or she has not made a difference in anyone's life, she gives herself up. For example, Durkheim (1897) found a higher suicide rate among Protestants compared to Catholics, arguing that stronger social control among Catholics results in lower suicide rates as Protestant society has a lower level of social integration than Catholic society.

- **Altruistic suicide** corresponds to too much social integration when individuals and

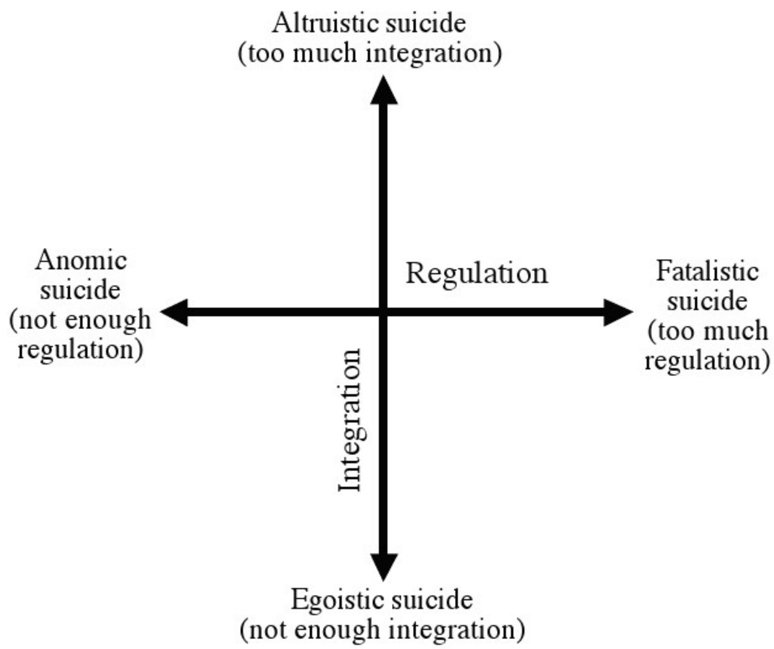


Figure 2: Durkheim's four types of suicide

the group are too close and intimate. This occurs when a group dominates the life of an individual to a degree where they feel meaningless to society. For example, in primitive times followers and servants ended their lives upon the deaths of their chiefs as a sacrifice. An example from the present time could be suicide bombers.

- **Anomic suicide** corresponds to a low level of social regulation. The sociological term anomie means a sense of despair or aimlessness due to the inability to expect life to be predictable. This type of suicide takes place due to certain breakdowns of social equilibrium, such as suicide after a social crisis. Society is temporarily incapable of exercising its regulative function, and the lack of constraints imposed on human aspirations makes happiness impossible. For instance, suicide occurs more in countries after periods of economic instability, like those of sudden prosperity or recession. Conversely, countries long immersed in poverty have enjoyed a relative immunity to self-inflicted death. On a micro level, an example can be suicide after bankruptcy or after winning a lottery.

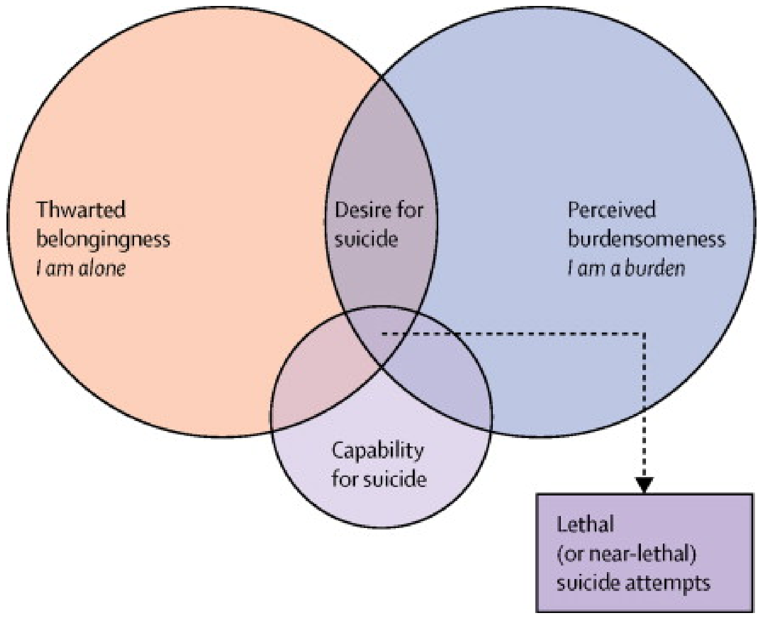
- **Fatalistic suicide** results from over-regulation in society. Under conditions of extreme social regulation, a person may elect to die rather than continue enduring the oppressive conditions due to a belief that there is nothing good to look forward to. Durkheim suggested this was the most likely motivator of suicides among prisoners.

Durkheim's theory of suicide has contributed much about the understanding of the phenomenon because of his stress on social rather than on biological or personal factors. His study has been extensively discussed by later scholars and supported by many empirical studies. For example, Danigelis and Pope (1979) provided empirical support to one of Durkheim's theory: the variance in social suicide rates can be explained by marital-familial status.

Durkheim's hypothesis that religion is an independent factor in studying suicide has also been validated. Case studies by Simpson and Conklin (1989) showed that Islam represents a high degree of fervor and integration among its followers and is associated with low suicide rates. Catholicism and Evangelical Protestantism tend to lower suicide rates, and Institutional Protestantism tends to increase them based on a statistical analysis of the U.S. county group suicide rates in 1970 (Pescosolido & Georgianna, 1989).

Several major criticisms to Durkheim's suicide theory have emerged. The main drawback of the theory is that he has laid too much stress only on one factor, namely the social factor and has ignored or minimized other factors, thereby making his theory only one-sided.

Figure 3: Interpersonal theory of suicide



Psychological theories are equally important theoretically and clinically since they provide a framework to understand how a complex interplay of factors combine to increase risk of suicide. O'Connor and Nock (2014) summarized predominant psychological models of suicidal behavior. Main motivation of suicide was the combination of stress, pain, perturbation (Shneidman, 1987), and to escape from painful self-awareness (Baumeister, 1990). Cognitive vulnerability is associated with stress and suicide risk (Schotte & Clum, 1987). The cognitive, affective, behavioural, and physiological system characteristics shape the development of suicide risk (Rudd et al., 2001). Williams's (2002) arrested flight model suggests that high feelings of defeat and entrapment and low potential for rescue (eg, social support) increase suicide risk.

The interpersonal theory of suicide has attracted considerable research attention in recent years. Figure 3 demonstrates the Van Orden et al. (2010)'s interpersonal theory of suicide, which emphasizes the coexistence of high levels of perceived burdensomeness and

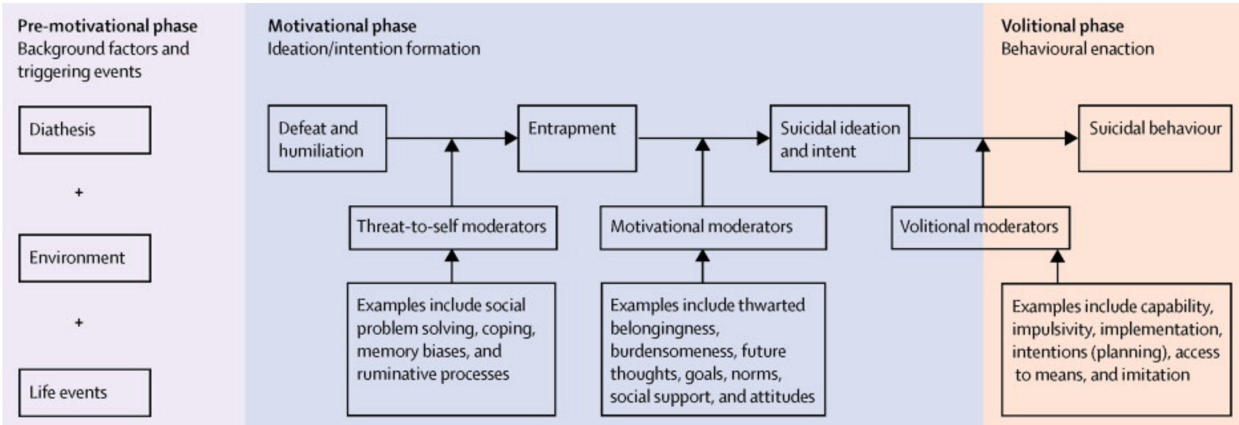


Figure 4: Integrated motivational-volitional model of suicide behavior

low levels of belongingness. Being in such a hopeless state leads to the development of suicidal desire, which is probably translated into suicidal behavior when capability is high. Acquired capability includes reduced fear of death and increased tolerance for physical pain. An individual's tolerance for physical pain increases through habituation such as exposure to and encounter with previous painful experiences. The Van Orden et al. (2010) theory has also been validated by empirical tests (Joiner Jr et al., 2009; Van Orden et al., 2008).

Integrating the key factors from earlier theories, O'Connor (2011) conceptualized the suicide process as a detailed map from thoughts to acts through motivational and volitional phases (figure 4).

Invoking the arrested flight model, when an individual feels defeated and trapped (unable to escape from stressful, humiliating, or defeating circumstances), she or he is more likely to emerge the suicidal ideation, when motivational moderators, for instance, low levels of social support, are present. The volitional moderators, including exposure to suicidal behavior of others, and having access to means of suicide, increase the likelihood of transferring suicidal ideation to action. The integrated motivational-volitional model builds on the pioneering research done by Williams (2002), Joiner Jr et al. (2009), and other scholars and it has been supported by empirical evidence.

Medical professionals consider suicide to be the result of depression and other psychiatric disorders. Psychologists look into the risk factors from cognitive theories to understand suicidal behavior and to develop strategies and interventions of suicide. Sociologists explain suicide as a product of social conditions. However, economists, as causal observers, explain suicide as an individual decision, and some suicides can be viewed as rational in the economic sense (Hamermesh & Soss, 1974; Mayo, 1986; Siegel, 1986; A. O. Ho, 2014).

The economic approach considers that a utility maximizing agent, confronting her own environments, chooses to commit suicide when it appears to be the most preferable alternative. The pioneering research of Hamermesh and Soss (1974) developed a framework to explain the suicide decision economically, which had numerous follow-up theories and empirical studies to explain suicide, including this work.

In their theory, when the present value of an agent's discounted lifetime utility falls below a certain threshold, she chooses to commit suicide. Two hypotheses are generated. An increase in permanent income reduces suicide due to the increasing utility with more income. In addition, the probability of suicide increases monotonically with age, as expected lifetime utility decreases as age increases, holding other factors constant.

This framework includes human capital as an additional determinant of expected utility, extended by Koo and Cox (2008). Unemployment depreciates human capital due to the lack of continuous job training. Thus, unemployment increases suicide rates by lowering not only the current income but also future income expectations through human capital depreciation.

The age hypothesis has been challenged by many researchers empirically (Cutler et al., 2009), especially when the age factor interacts with unemployment. Middle-aged people, as the group with the most severe depreciation in human capital, suffer the most when unemployed since they are likely to take longer to adjust to new labor market conditions. Hence, age relates to suicide non-monotonically due to the difference in the rate of human capital depreciation (Koo & Cox, 2008).

From the real option perspective, Dixit and Pindyck (2012) introduced the "option value" of staying alive and waiting to see if the situation will improve into the decision-making process of committing suicide. This is similar to the choice-making process when an investor has the option to hold the investment for a while and wait to see what will happen in the future under conditions of uncertainty and irreversibility. A person contemplating suicide might be convinced by such a prospect to postpone the irreversible act.

Building on this concept, Becker and Posner (2004) developed an advanced model of suicide. The model accounts for the risk-taking implications of the utility maximization approach, assuming that utility is maximized sequentially over time with the option value from delaying suicide. The model backed up the non-monotonic relationship between age and suicide: the opportunities from life are more favorable for young people compared to older people in similar situations. Thus, young people commit suicide less than other age groups since waiting has a higher option value for them. Contrarily, Miao and Wang (2011) argued young people are more likely to commit suicide due to the low option value of staying alive.

Using comparative statics to understand how different parameters of the income distribution change the wage threshold below which an individual commits suicide, Suzuki (2008) modeled the mean of future income as a negative factor to such threshold. In addition, an increase in the variance of income has two effects: (a) reducing the expected utility of risk-averse individuals and (b) increasing the option value to postpone suicide decisions. He found that the likelihood to commit suicide increases monotonically with the variance of income, which means the former effect dominates.

An individual will not die by suicide unless he or she has both the desire to die by suicide and the ability to do so both mentally and physically (Joiner, 2005). Joiner's interpersonal–psychological theory of suicidal behavior indicates two overarching hypotheses: (a) the perceptions of burdening others and of social alienation combine to instill the desire for death and (b) individuals will not act on the desire for death unless they have developed the capability to do so. Such capability develops through exposure and thus habituation to painful and/or fearsome experiences. On the other hand, easy access to lethal means provides physical accessibility and instrumentality to suicide. From a theoretical perspective, economists can argue that easy access to lethal means lowers the costs of suicide, increasing the number of suicides as a result. However, there has been no published economic study establishing this association, despite this clear implication, mainly due to a lack of individual-level data.

Although lacking empirical evidence of this hypothesis, a few studies in psychology, public health, and criminology present discussions on suicide prevention through limiting access to lethal instruments (Brent et al., 1991; Kellermann et al., 1991; Lester & Clarke, 1989). In contrast, concerns exist that simply limiting the access to one particular means of committing suicide drives people to use alternative means and therefore does not actually prevent suicide. Whitman (2002) proposed a dynamic search model of suicide which suggests that if the cost of committing suicide in the future decreases, for instance with a limitation in a method's availability, the person who wants to commit suicide may become more willing to employ a more costly method in the present, which may lead to an upsurge in the suicide rate.

Suicide contagion has been a noteworthy subject of study for centuries, which is a social phenomenon that happens when one suicide instills suicide attempts by other people. In practice, it is difficult to identify whether one suicide was influenced by another one unless a will is found or some pre-announcement has been made. A cluster of suicides within a short period is often considered contagious suicide. When a particular suicide becomes widely known, similar suicides or suicide attempts in terms of means employed or otherwise, drawing disproportionately more attention from the community, spurring copycat behavior. Hence, the WHO issued media guidelines on reporting suicide news in 2000.

Studies discuss when suicide can be contagious, rather than constructing a model or developing economic theories to explain this phenomenon. When an individual commits suicide, the group to which he or she belonged experiences grief and stress, which may precipitate other suicides. It is essential to recognize which cases of suicides may prompt similar acts for suicide prevention purposes (Cutler et al., 2009).

Along these lines, Chen et al. (2012) suggested taking some negative externality of suicide into account, when modeling the grief-and-stress story, based on Hammermesh and Soss's framework. Moreover, the evolutionary game theory on contagion and social learning can be valuable as a potential theoretical framework to model copycat suicides. Further studies are needed from theoretical perspectives.

There are abundant economic theories to study suicide from its socio-economic dimensions. It is important to study suicide by employing a rational approach that complements the psychological and medical perspectives on suicide. The next subsection reviews a variety of empirical works on suicide to provide some evidence-based perspectives.

Table 1 summarizes a variety of empirical studies on suicide behavior in the general population. Most literature uses suicide rate as the dependent variable aggregated at the country, regional (e.g., state and county), or group level, due to the extremely low accessibility of individual-level data on decisions to commit suicide. Studies in table 1 include several types of suicide rates of the general population such as total suicide rates, standardized suicide rates, both in the unit of per 100,000 people. Others use the natural logarithm of suicide rate. Some studies use youth suicide rates, denoted by a subscript y. Many works attempt to explain the relationship between gender-related socio-economic factors and suicide, which are not included in the table. The first column lists diverse socio-economic variables as the independent variables. The sign indicates the association between the factor and suicide rates, where only the statistically significant relationships are included in the table. However, the empirical results are not necessarily robust and consistent. Table 1 mainly focuses on presenting mixed results on the effects of various factors on suicide in the empirical literature. The reason for such inconsistent results may include the different data sets employed, different estimation approaches operated, the list of covariates included, and so on. The discrepancy in views and conflicting evidence underlines the need for further studies.

As introduced in the previous subsection, Hamermesh and Soss (1974) proposed a model based on the following income hypothesis: an individual decides to commit suicide when his or her discounted expected lifetime utility falls below a certain threshold. High income can exchange abundant resources, which is likely to be associated with wealthier

Table 1: Summary of Estimation Results from Selected Empirical Studies on Suicide

Dependent variable: suicide rates Explanatory variables	Sign	Citation
Economic factors		
Income	$-$	(Barnes, 1975; Kimenyi & Shughart, 1986; Faupel et al., 1987; Chuang & Huang, 2003; Daly & Wilson, 2006; Helliwell, 2007; Cutler et al., 2009)
	$+$	(Simpson & Conklin, 1989; Chew & McCleary, 1995; Lester, 1995)
	$-_y$	(Mathur & Freeman, 2002; Cutler et al., 2009)
	$+_y$	(Freeman, 1998)
Income inequality	$+$	(Freeman, 1998; Daly & Wilson, 2006; Chen et al., 2009)
Economic growth	$+$	(Burr et al., 1994)
Education	$-$	(Klick & Markowitz, 2006; Daly & Wilson, 2006)
	$+$	(Barnes, 1975; Faupel et al., 1987; Marcotte, 2003)
Unemployment	$+$	(Kimenyi & Shughart, 1986; Faupel et al., 1987; Huang, 1996; Freeman, 1998; Mathur & Freeman, 2002; Chuang & Huang, 2003; Klick & Markowitz, 2006; Daly & Wilson, 2006)
Demographic factors		
Age	$+$	(Ford & Kaserman, 2000; Marcotte, 2003; Daly & Wilson, 2006)
Proportion of elderly	$+$	(Simpson & Conklin, 1989; Chuang & Huang, 2003)
Proportion of youth	$+$	(Mathur & Freeman, 2002; Helliwell, 2007)
	$-$	(Mäkinen, 1997)
Gender (Male)	$+$	(Ford & Kaserman, 2000; Daly & Wilson, 2006)
Ethnic heterogeneity	$+, +_H, +_W, +_B$	(Burr et al., 1994; Mathur & Freeman, 2002; Marcotte, 2003; Neumayer, 2003; Daly & Wilson, 2006)
	$-_B, -_H, -_O$	(Faupel et al., 1987; Daly & Wilson, 2006; Cutler et al., 2009)
Cohort effect	$+$	(Solomon & Hellon, 1980; Murphy & Wetzel, 1980; La Vecchia et al., 1986; Moens et al., 1987; Skegg & Cox, 1991; Granizo et al., 1996; Allebeck et al., 1996; Gunnell et al., 2003)

Table continues on the next page

Summary of Estimation Results from Selected Empirical Studies on Suicide, continued

Dependent variable: suicide rates		
Explanatory variables	Sign	Citation
Household related factors		
Divorce rate	$+,$	(Kimenyi & Shughart, 1986; Faupel et al., 1987; Burr et al., 1994; Lester, 1995; Mäkinen, 1997; Freeman, 1998; Whitman, 2002; Mathur & Freeman, 2002; Chuang & Huang, 2003; Helliwell, 2007; Minoiu & Andres, 2008; Chen et al., 2009; Cutler et al., 2009)
	$+_y$	(Cutler et al., 2009)
	$-, -_F$	(Rodriguez, 2006)
Marriage rate	$-, -_M, -_F$	(Neumayer, 2003; Daly & Wilson, 2006; Maag, 2008)
	$+_M$	(Maag, 2008)
Fertility rate	$-$	(Faupel et al., 1987; Mäkinen, 1997; Mathur & Freeman, 2002; Rodriguez, 2006)
	$-_M, -_F$	(Mäkinen, 1997; Neumayer, 2003; Rodriguez, 2006; Koo & Cox, 2008)
Average household size	$+$	(Daly & Wilson, 2006)
	$-_F$	(Neumayer, 2003)
One-person households	$+$	(Faupel et al., 1987; Burr et al., 1994)
	$-$	(Daly & Wilson, 2006; Helliwell, 2007)
(social isolation)		
Health factors		
Alcohol/drug consumption	$+$	(Mathur & Freeman, 2002; Rodriguez, 2006; Chen et al., 2009)
	$-_M, +_F$	(Rodriguez, 2006)
Health care cost	$+$	(Kimenyi & Shughart, 1986; B. Yang & Lester, 1993)
Suicide prevention programs	$-$	(Miller et al., 1984; Chuang & Huang, 2003)
Other factors		
Religion	$-$	(Faupel et al., 1987; Simpson & Conklin, 1989; Burr et al., 1994; Helliwell, 2007)
Suicide attempt	$+$	(Marcotte, 2003)
Covid	$+$	(Sher, 2020)

life standards and better satisfaction from living. People with higher income, on the other hand, can better cope with life's stressful events and difficult circumstances. Accordingly, an individual with a higher income is likely to achieve higher utility, diminishing the probability of committing suicide. Most studies use variables such as per capita real income, per capita real GDP, median family income, and/or average growth rate of real income to capture the average economic characteristics of the observed group and indeed find a negative association between income and suicide rates.

Nevertheless, the direct causality between the economic situation of an individual and her decision to commit suicide is not necessarily explained, since the data are not at the individual level but country or group average level. Some studies find lower income associated with lower suicide rates. Blanchflower and Oswald (2004) argued that economic prosperity is unrelated to happiness or general welfare. This result can be supported by Durkheim (1897)'s theory that people with low income may leave themselves to their economic situation and passively accept their lives. The probability of suicide behavior can be reduced by such a coping mechanism.

It is also plausible that the positive relationship between income and suicide is due to different data selection, different empirical approaches, or omitted variable bias. In addition, without the inclusion of an income dispersion variable, the income variable may have captured the effect of income inequality, and resulted in this positive association (Burr et al., 1994; Freeman, 1998).

In addition to aggregated income or average income, the distribution of income also affects decisions to commit suicide. Relatively poor individuals may experience more stress, leading to insufficient health conditions and ending directly or indirectly, for instance, through alcohol abuse or smoking, in suicide. Most researchers agree that income inequality leads to higher suicide rates (Freeman, 1998; Daly & Wilson, 2006; Chen et al., 2009).

It is worth mentioning that some studies point out that the impact of income can be asymmetric across age-gender groups and the degree of urbanization. Chen et al. (2009) showed that, while income is negatively associated with suicide rate across all age-gender groups, its impact is more significant in males between 45 and 64 years of age and females over 65 years old. Huang (1996) and Rodriguez (2006) indicated the significance of income for females, whereas Neumayer (2003) and Minoiu and Andres (2008) demonstrated its significance only for males. (Faupel et al., 1987) argued that the effect of median family income on suicide rate is significantly negative, especially in the most urban and medium urban counties of the United States but not in the least urban counties.

Some literature considers education level as one of the important determinants of income. A high level of education may be indirectly associated with a lower suicide rate through better jobs and higher income. It may be directly associated with a lower suicide rate because of higher levels of life satisfaction.

On the other hand, a high level of education may be associated with a higher suicide rate due to lower adherence to religious beliefs and a greater tendency towards materialism and individualism, which may weaken the bond between an individual and society. Moreover, people with higher education may experience higher levels of frustration and stress because of increasing difficulties in research and work, leading to higher suicide rates. For example, graduate students experience significant amounts of stress and anxiety, and their suicidal behavior is strongly characterized by depression, hopelessness, desperation, lack of control, and eating problems (Garcia-Williams et al., 2014). Existing studies showed mixed results and the impact of education level on suicide rates are gender-age-region specific (Barnes, 1975; Faupel et al., 1987; Klick & Markowitz, 2006; Daly & Wilson, 2006).

Unemployment, as a predictor of future earnings, signals a decrease in income. Therefore, according to the framework of Hamermesh and Soss (1974), the rising unemployment rate should lead to an increase in the occurrence of suicide and suicide attempts. There is extensive literature on unemployment and suicidal behavior; Platt (1984) has exhaustive reviews on this issue with the conclusion that there is an increased risk of suicide and deliberate self-harm among the unemployed. Unemployment can be associated with mental and/or physical illness, which could lead to suicide.

Many economic studies also found that a high unemployment rate tends to be associated with a high suicide rate (Kimenyi & Shughart, 1986; Faupel et al., 1987; Burr et al., 1994; Huang, 1996; Mäkinen, 1997; Freeman, 1998; Chuang & Huang, 2003; Klick & Markowitz, 2006; Daly & Wilson, 2006; Koo & Cox, 2008).

Being consistent with the hypothesis that economic crisis is associated with a high suicide rate, financial stress during economic crises involves bankruptcies and hence unemployment. For example, both personal bankruptcy and firm bankruptcy have a significantly positive effect on male and female suicide rates in Japan (Watanabe et al., 2006).

Different factors to suicide are considered heterogeneous across different age, gender, and ethnic groups. For example, age is positively associated with suicide since older people are more likely to experience physical health problems and mental issues such as anxiety or loneliness from living alone or after the death of their close ones. Countries with a high percentage of elderly (over 65 years old) tend to have high suicide rates (Simpson & Conklin, 1989). On the other hand, youth are vulnerable to family issues such as parents' separation, divorce, violence, and abuse. Some studies argue that age is negatively associated with suicide rates. Faupel et al. (1987) show that the median age is negatively associated with the suicide rate in most urban counties. Mäkinen (1997) argued that the percentage of young people under 15 years old has a significantly negative correlation with the suicide rate.

The discrepancy between male and female suicide rates is well demonstrated in the literature. A significant amount of studies show that males in general are at a higher risk of suicide than females (Lewis & Sloggett, 1998; Ford & Kaserman, 2000; Chuang & Huang, 2003; Daly & Wilson, 2006; Helliwell, 2007). More young males than young females successfully commit suicide, but more young females attempt suicide (Cutler et al., 2009).

In terms of the race heterogeneity in suicide, many studies show that the black population is at a lower risk of suicide than other populations (Faupel et al., 1987; Neumayer, 2003; Daly & Wilson, 2006). Communities with higher levels of ethnic heterogeneity are likely to have higher suicide rates (Neumayer, 2003) since rapid colonization and social disintegration lead to anomie, low self-esteem, and despair.

Cohort analysis is an important tool for studying suicide. Individuals in the same cohort share experiences such as economic fluctuation and social events, leading to cohort-specific behavior. For example, successive birth cohorts in the United States carry successively higher suicide risks as they age (Murphy & Wetzel, 1980). A similar phenomenon is observed in some industrialized countries, such as Canada (Solomon & Hellon, 1980), Italy (La Vecchia et al., 1986), Belgium (Moens et al., 1987), New Zealand (Skegg & Cox, 1991), Sweden (Allebeck et al., 1996), Spain (Granizo et al., 1996), and England and Wales (Gunnell et al., 2003).

According to Durkheim's theory, social isolation, disintegration, and disconnectedness lead to suicide. Household-related factors play important roles in suicide decisions as they reflect changes in the degree of social integration.

For example, marriage is a proxy for social integration. Daly and Wilson (2006) demonstrate that the proportion of married people has a significantly negative impact on suicide rates in aggregate data while that of single or never married people has a significantly positive impact on suicide rates in the individual-level data. Oppositely, divorce represents receding social integration and family ties, which can induce stress, shame, pain, and other mental issues. Divorce may lead to risky behaviors such as suicide in extreme scenarios. Numerous studies point out a strong, and positive relationship between suicide and divorce. Economic studies find that higher divorce rates are associated with higher suicide rates (Kimenyi & Shughart, 1986; Faupel et al., 1987; Burr et al., 1994; Lester, 1995; Mäkinen, 1997; Freeman, 1998; Chuang & Huang, 2003; Neumayer, 2003; Helliwell, 2007; Minoiu & Andres, 2008).

The impact of divorce differs across age and gender groups, as well. The increased proportion of youth living in a home with a divorced parent is the most essential factor explaining the rise of youth suicide (Cutler et al., 2009). Men are more sensitive to negative mental influences from divorce. Studies find that the male suicide rate is more sensitive to divorce than the female suicide rate (Neumayer, 2003; Rodriguez, 2006; Watanabe et al., 2006; Koo & Cox, 2008). Moreover, Chen et al. (2012) argue that marriage may benefit men more significantly than women. In this case, the loss of the benefits after divorce is likely to affect men more than it would affect women. In addition, the increasing divorce rate may encourage women to become independent mentally and financially to pursue freedom and to seek identity. Therefore, divorce rates are likely to be associated with lower female suicide rates.

From a social point of view, the birth rate is a proxy for improving the level of social integration. From the household perspective, giving birth brings joy, satisfaction, excitement, and self-esteem to a family. There is no doubt that theoretically a high birth rate is associated with a low suicide rate. Indeed, most studies indicate that a high birth rate is corresponding to lower suicide risk, which empirically supports the negative association between social integration and suicide rates (Durkheim, 1897; Faupel et al., 1987; Mäkinen, 1997; Rodriguez, 2006; Koo & Cox, 2008). However, childcare may cause stress and create an economic burden on low-income households. Some studies present a positive correlation between birth rate and suicide rates (Lester, 1995; Chen et al., 2009).

Opposite to birth rate, migration is considered to decrease the level of social integration due to the weakening of community ties, such as separation of families and friends, and work detachment. It is also challenging adapting to a new environment, especially when migrants become a minority in society. Migrants tend to encounter various difficulties such as loss of identity, cultural shock, unemployment, and even poverty, which may put their mental health at risk. Studies show that migration rate is positively associated with the suicide rate (Faupel et al., 1987; Lester, 1995). On the other hand, (Chuang & Huang, 2003) argue that a large in-migration population is associated with a lower suicide rate, as a representation of an upscale quality of life.

Population growth or population density is regarded as a proxy for modernization, which may reduce social integration. People may experience stronger loneliness and more severe anxiety in more urbanized and industrialized societies. Therefore, higher population density increases suicide rates (Burr et al., 1994). Regardless, other studies show modernization is negatively associated with suicide rates (Zhang, 1998; Minoiu & Andres, 2008).

Household size is a good proxy for the level of social isolation. Studies also use one-person households as the explanatory variable to model the relationship between social isolation and suicide. Results show that a bigger household size reduces female suicide rates (Neumayer, 2003), and suicide rates in general (Qin, Agerbo, & Mortensen, 2003). In addition, a higher proportion of one-person households indicates higher suicide rates in metropolitan areas (Burr et al., 1994). However, both Chuang and Huang (2003) and Daly and Wilson (2006) find a negative association between the proportion of widowed people and suicide rates, in Taiwan and the U.S., respectively. They argue that the part of the long-existing widow population may have already built up strong resilience, which results in a lower risk for suicidal behavior than the widows who have just lost their husbands.

It is universally acknowledged that health issues are one of the most important motivations for committing suicide, not only because of the physical pain that a person experiences when ill, but also the mental stress and economic burden that often accompanies illness. Studies show that the ratio of health care cost to CPI increases suicide rates (Kimenyi & Shughart, 1986; B. Yang & Lester, 1993). Mental health problems such as depression, drug dependence, and alcohol consumption are positively associated with suicide (Neumayer, 2003; Rodriguez, 2006; Chen et al., 2009). On the other hand, worldwide suicide crisis intervention services and suicide prevention programs have been effective in reducing suicides. Studies provide supporting evidence to emphasize the importance of the accessibility of services (Miller et al., 1984; Chuang & Huang, 2003).

According to Durkheim's integration view, people in general with higher levels of religious affiliation are more likely to be at lower risk for suicide. Many religions prohibit or stigmatize suicide. Studies support the hypothesis that countries and areas with high levels of religiosity tend to have lower suicide rates (Faupel et al., 1987; Simpson & Conklin, 1989; Burr et al., 1994; Helliwell, 2007). Certain religions are considered more effective than others in promoting social integration and preventing suicide. For instance, in Durkheim's view, Catholic communities have lower suicide rates than Protestant ones, due to the feature that Catholicism emphasizes more against suicide, while Protestantism underlines the spirit of free inquiry and is less integrated. Islamic communities have lower suicide rates than others since Islam prohibits suicide (Durkheim, 1897).

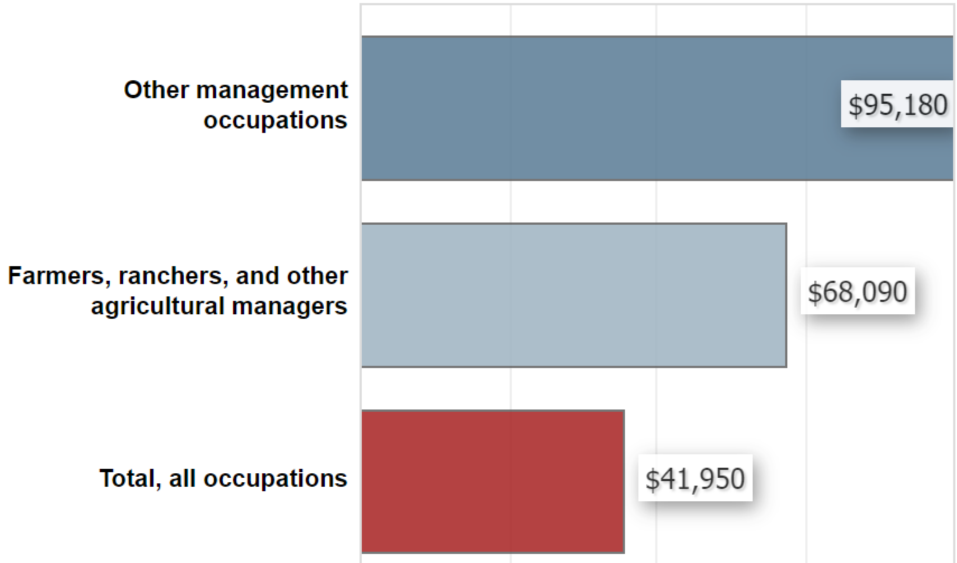
Studies indicate that the COVID-19 pandemic is associated with distress, anxiety, fear of contagion, depression, and insomnia in the general population and among healthcare professionals. The COVID-19 crisis may increase suicide rates during and after the pandemic (Sher, 2020).

2.1.2 Relevance to farmers

A better understanding of the major socio-economic factors of suicide among the general population sets the stage for our exploring the reasons for farmer suicide. In this section, I briefly discuss the factors that are likely to be relevant to farmers to draw inferences on why farmers commit suicide.

Farmers, ranchers, and other agricultural managers in the U.S. earned an average of \$56,514 in 2019, \$990 more than than the average national salary of \$55,524 (United States Census Bureau, 2020). The median annual wage for farmers, ranchers, and other agricultural managers was \$68,090 in May 2020, \$26,140 more than the median annual wages of the people working in all occupations in the U.S. Economy (Bureau of Labor Statistics, 2020). Detailed comparison is shown in figure 5.

Figure 5: Median annual wages comparison, May 2020



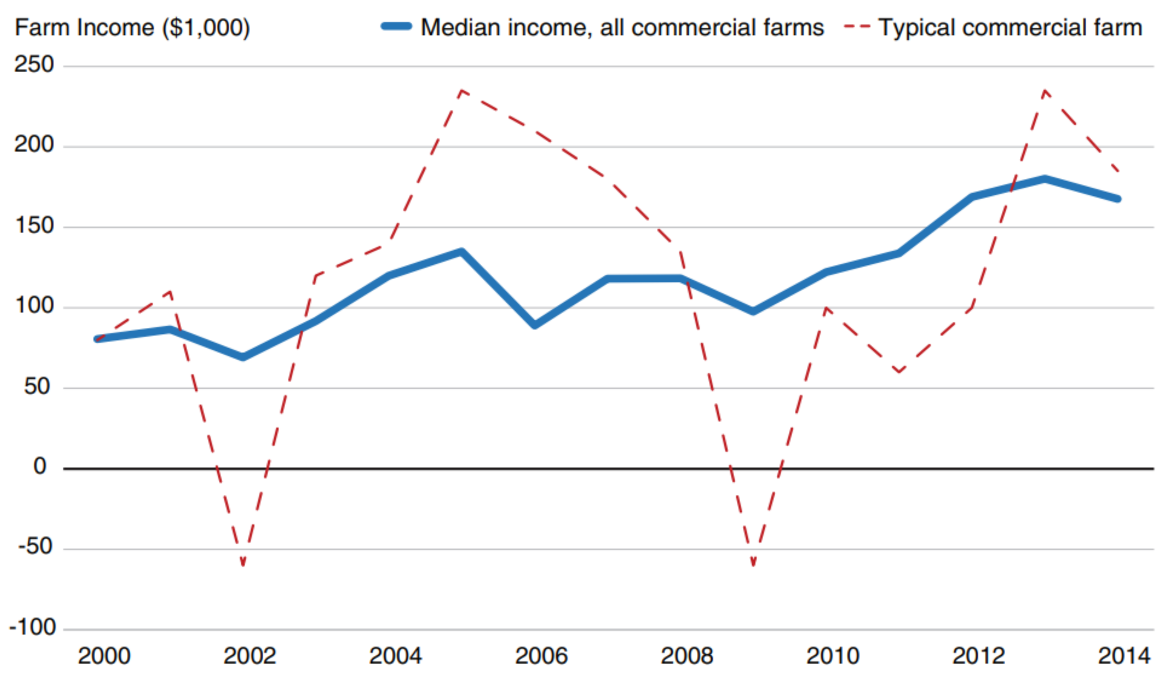
Source: U.S. Bureau of Labor Statistics, Occupational Employment and Wage Statistics

However, most researchers agree that the variability of income, rather than the levels of income, plays a significant role in suicide decisions (Freeman, 1998; Daly & Wilson, 2006; Chen et al., 2009). For example, stable low income may be associated with low suicide rates due to the coping mechanism (Blanchflower & Oswald, 2004).

Farmers' income is variable due to fluctuations in input and output prices, unpredictable weather, and high risks of illness and injury in agricultural production activities. Such variability influences fundamental farm decisions including the choice of crops or livestock to produce, how much income to allocate to costs like irrigation or pesticides, the amount of labor to use on-farm, and how much to save to reduce future risks. Unlike people working in other occupations, whose salaries mostly go to daily expenses and savings, farmers have to invest part of their income into the next production period to generate income in the next cycle. Such flow is highly vulnerable to unpredictable events. Once the cash flow breaks, it is likely to cause snowballing effects of destructive consequences that carries forward into future periods.

The difference between aggregate and individual farm income variability is presented in figure 6, reproduced from a study of Key et al. (2017). This study focused on commercial farms with at least $350,000 in gross cash farm income, adjusted for inflation, which are responsible for about 80 percent of U.S. agricultural output. The median income of farms (represented by the blue line) over the period varied less than the income of a typical commercial farm, represented by the red dashed line. The income stream of the hypothetical farm is more volatile compared to the aggregated median farm with a swing of $86,000 on average, albeit they have the same average income during the study period.

Figure 6: Aggregate and individual farm income variability, 2000-2014



Source: USDA ERS, and USDA NASS 1996-2013, and USDA, Census of Agriculture, 2014 Tenure, Ownership, and Transition of Agricultural Land Survey

Key et al. (2017) find the following five determinants of farm income variability: main type of commodity produced, the size of the farm (operation), education level and marital status of the farmer (operator), and whether farming is the primary occupation of the farmer. Crop farms are more likely to have volatile income than livestock farms, likely due to the fact that crops are more vulnerable to weather and pests.

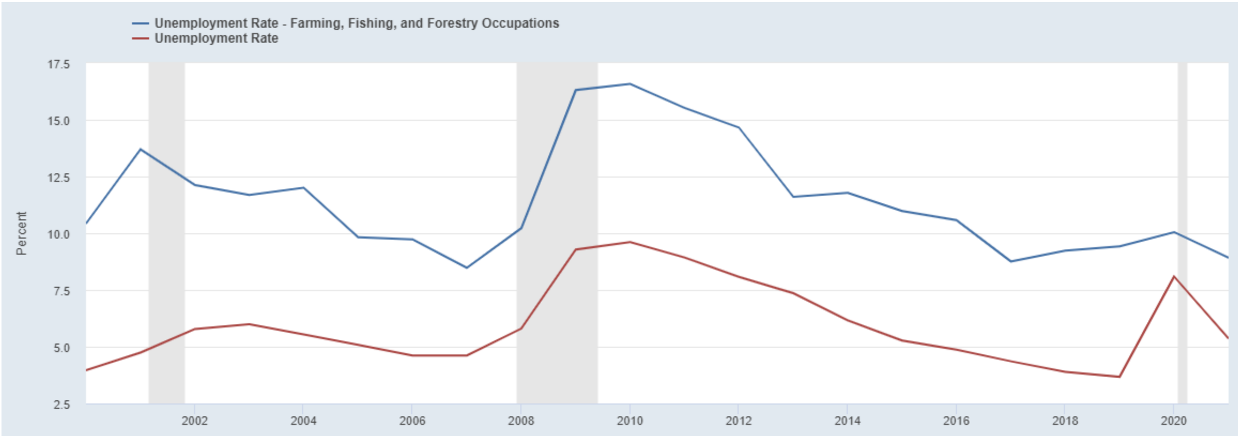
Households with larger farm operations have more volatile income than those with smaller operations in terms of asset value. The positive correlation between farm size and income volatility may be because the larger farms generate a greater share of their total income from the farm.

The volatility of farm income is considerably lower when the principal farmer has more years of education. Less-educated workers, in general, face a higher risk of unemployment than better-educated workers. Given that the study period spanned the Great Recession in the U.S., one of the contributing factors to the negative association between education and income variability could be that less-educated farmers are more likely to face difficulties in coping with the challenges of economic recessions. In addition to being a proxy of income variability, unemployment is one of the factors positively associated with suicide. People working in farming, fishing, and forestry occupations had higher unemployment rates on average than the unemployment rate of the U.S. labor force from 2000 to 2021, as shown in figure 7. The constant high unemployment rate among farmers indicates that farmers are at higher risk of suicide than people working in other occupations.

The income volatility is substantially higher among the farmers who report farming as their primary occupation than those who did not farm full time. Full-time farmers derive most of their total earnings from farm income, which is more variable than off-farm income.

In addition, being married is associated with a decrease in farm income volatility.

Figure 7: Annual average unemployment rate of farmers and the U.S. labor force, 2000-2021



Source: U.S. Bureau of Labor Statistics

Note: Shaded areas indicate U.S. recessions.

Married couples operating a farm likely earn a more substantial share of household income from less volatile off-farm sources compared with single farm operators.

Unexpected global negative events, such as the COVID-19 pandemic, are associated with farm income volatility. According to USDA ERS, farm businesses experienced turmoil in production because of lowered availability of labor and other inputs, and output prices were affected by changes in demand for commodities in certain market segments.

In summary, although farmers, ranchers, and other agricultural managers earn decent wages on average, their highly variable income can be a contributing factor to farmer suicide since their incomes depend on various factors beyond their control. It is important to understand the sources of farm income variability and decompose the variability into components associated with the vulnerability of farmers that could potentially lead to suicide.

In addition to factors associated with income variability, other factors may also be relevant to farmer suicides. Multiple studies show that age is positively associated with suicide. The average age of male farmers, ranchers, and other agricultural managers is 50.2, and male employees are generally 1.93 years older than their female counterparts (Bureau of Labor Statistics, 2021). According to the Census of Agriculture in 2017, 58% of the farmers, both farm managers, and non-managers, were between 35 and 64 years old, and 34% of them are older than 65 years old. The statistics reveal the concern that farmers, in general, are at a high risk of suicide, not only due to the fact that they are older but also because of the increasing likelihood of mental and physical breakdowns associated with aging. The decrease in abilities along with aging also causes difficulties in farming.

A number of studies show that males are at a higher risk of suicide than females. The majority of the farmer population in the U.S. is male. In fact, 85.1% of farmers, ranchers, and other agricultural managers are male on average since 2014. The percentage of male producers, including farm managers and non-managers, is 64%, according to the USDA Census of Agriculture in 2017. Regarding ethnic groups, some studies find a positive association between ethnic whites and suicide. In 2019, 92.47% of farmers, ranchers, and other agricultural managers were White (85.2% non-Hispanic plus 7.27% Hispanic), making that the most common race or ethnicity in the occupation. 95.4% of farmers, managers, and non-managers together, are White. As a comparison, 61.3% of the people in the labor force are White (non-Hispanic).

The birth rate is negatively associated with suicide due to newborn babies bringing hope and joy to families. Since farmers are older, Farmers are less likely to have young children in their families. Due to the same reason, farmers are likely to have a smaller household size, which is also positively associated with suicide. Furthermore, the majority of farmers live in rural areas, where access to mental services and suicide prevention programs are limited.

In addition to psychological and socio-economic factors, climate change can be a primary factor of farmer suicide because farmers are exposed to weather events during farming activities. Farm profits also highly depend on weather conditions. The next section introduces studies on identifying exogenous weather factors to explain suicide and depression among the general population.

2.2 Impact of climate change on the general population

Suicide has long been observed to vary with weather. There is rich literature concerning the effects of climatic conditions on depression and suicide in different countries around the world since suicide alone causes more deaths globally than all forms of interpersonal and inter-group violence combined (Lim et al., 2012). Thus, it is crucial to determine whether or not the suicide rate responds to climatic conditions. Elucidating the relationships between climatic factors and mental health will not only improve people's understanding of suicide but also will help facilitate adaptation to climate change.

Many studies attributed variations in the suicide rate of the general population to climate factors, including temperature (P. G. Dixon et al., 2007; Souêtre et al., 1990; Preti, 1998; Marion et al., 1999; Deisenhammer et al., 2003; Ajdacic-Gross et al., 2007; Carleton, 2017; Burke et al., 2018), sunlight exposure (Preti, 1998; Ajdacic-Gross et al., 2007; Tsai, 2010), and precipitation (Deisenhammer et al., 2003; Preti, 1998; Ajdacic-Gross et al., 2007; Nicholls et al., 2006; Hanigan et al., 2012). Table 2 summarizes factors identified in the literature as contributing to variations in the rate of suicide.

Table 2: Summary of estimation results from selected empirical studies on suicide and weather conditions

Factors	Sign	Country or region (citation)
Common factors		
Temperature	+	France (Souêtre et al., 1990), Canada (Marion et al., 1999), Austria (Deisenhammer et al., 2003), Taiwan (H. C. Lee et al., 2006), Switzerland (Ajdacic-Gross et al., 2007), England and Wales (Page et al., 2007), East Asian (South Korea, Japan, Taiwan) (Y. Kim et al., 2016), United States (P. G. Dixon et al., 2007), Finland (Ruuhela et al., 2009), India (Carleton, 2017), United States and Mexico (Burke et al., 2018)
	−	Taiwan (Tsai, 2010)
	0	United States, California (Tietjen & Kripke, 1994), United States (P. G. Dixon et al., 2007), South Australia (Lambert et al., 2003)
Sunlight	+	France (Souêtre et al., 1990), Belgium (Maes et al., 1994), UK (Salib & Gray, 1997) , World (20 countries) (Petridou et al., 2002), Southern Australia (Lambert et al., 2003), Greece (Papadopoulos et al., 2005), Chile (Heerlein et al., 2006), Taiwan (Tsai, 2010)
	−	Italy (Wehr & Rosenthal, 1989), United States, California (Tietjen & Kripke, 1994), Italy (Preti et al., 2000)
	0	Italy (Wehr & Rosenthal, 1989; Preti et al., 2000), Switzerland (Ajdacic-Gross et al., 2007)
Precipitation	+	Taiwan (Tsai, 2010)
	−	Italy (Wehr & Rosenthal, 1989; Preti, 1998), Austria (Deisenhammer et al., 2003), Australia (Nicholls et al., 2006; Hanigan et al., 2012)
	0	Southern Australia (Lambert et al., 2003), Switzerland (Ajdacic-Gross et al., 2007), Finland (Ruuhela et al., 2009), India(Carleton, 2017)
Other factors		
Thunderstorm	+	Austria (Deisenhammer et al., 2003)
Atmosphere pressure	+	Austria (Deisenhammer et al., 2003),
Solar radiance	+	Greece (Papadopoulos et al., 2005)
Humidity	−	UK(Salib & Gray, 1997) ,Italy (Wehr & Rosenthal, 1989), Austria (Deisenhammer et al., 2003)
Air pollution	+	South Korea (C. Kim et al., 2010), Taiwan (A. C. Yang et al., 2011), United States, Utah (Bakian et al., 2015)
Latitude	+	Italy (Wehr & Rosenthal, 1989)

Table continues on the next page

Table 2 continued

Factors	Country or region (Citation)
Suicide seasonality	
Spring-Summer peak	North hemisphere high latitude countries: Greenland (Björkstén et al., 2005, 2009), Norway (Morken et al., 2002), Ireland (Corcoran et al., 2004), Finland (Hakko et al., 1998; Räsänen et al., 2002; Partonen, Haukka, Nevanlinna, & Lönnqvist, 2004; Partonen, Haukka, Pirkola, et al., 2004; Partonen, Haukka, Viilo, et al., 2004; Hiltunen et al., 2011)
	Relative low latitude countries: United States (Kposowa & D'Auria, 2010), France (Souetre et al., 1987; Souêtre et al., 1990), Italy (Altamura et al., 1999; Preti, 1998; Preti et al., 2000; Rocchi et al., 2007), Belgium (Maes et al., 1993), Switzerland (Ajdacic-Gross et al., 2005) , Lithuania (Kalediene et al., 2006), Slovenia (Oravecz et al., 2007), Japan (Nakaji et al., 2004), China Hong Kong and Taiwan (T. P. Ho et al., 1997)
Reciprocal summer-months peak	South hemisphere: Australia (Cantor et al., 2000; Lambert et al., 2003; Rock et al., 2003; Law & De Leo, 2013), Chile (Retamal C & Humphreys, 1998; Heerlein et al., 2006), South Africa (Flisher et al., 1997)
No effect	Equatorial regions (Parker et al., 2001; Heerlein et al., 2006; Benedito-Silva et al., 2007; Nejar et al., 2007)

Early work of statisticians identified seasonality of suicide: suicide frequencies are higher in late spring and summer than in the winter months (Durkheim, 1897), although it seems to be counter-intuitive given the impression of most people that their mood deteriorates during fall and winter. Social and bio-psychiatric research assumed that heat-related excitability of the nervous system triggers suicide and that explained the more frequent suicide occurrence in warm months (Kevan, 1980; K. W. Dixon & Shulman, 1983). Early work focused mainly on weather conditions such as temperature, precipitation, duration of daylight, cloud cover, humidity, winds, and air pressure. The preliminary statistical investigations suggested that it was not heat per se but the change (increase) of temperature in spring that yielded a cyclical increase of suicide frequencies (Souetre et al., 1987; Souêtre et al., 1990; Maes et al., 1993; Salib & Gray, 1997; Preti, 1998; Marion et al., 1999; Petridou et al., 2002).

Recent empirical studies consistently observed the spring to summer peak in suicide in northern countries such as Greenland (Björkstén et al., 2005, 2009), Norway (Morken et al., 2002), Ireland (Corcoran et al., 2004), Finland (Hakko et al., 1998; Räsänen et al., 2002; Partonen, Haukka, Nevanlinna, & Lönnqvist, 2004; Partonen, Haukka, Pirkola, et al., 2004; Partonen, Haukka, Viilo, et al., 2004; Hiltunen et al., 2011). In countries of lower latitudes, this seasonal pattern also persists. For example, seasonality was observed in United States (Kposowa & D'Auria, 2010), France (Souetre et al., 1987; Souêtre et al., 1990), Italy (Altamura et al., 1999; Preti, 1998; Preti et al., 2000; Rocchi et al., 2007), Belgium (Maes et al., 1993), Switzerland (Ajdacic-Gross et al., 2005) , Lithuania (Kalediene et al., 2006), Slovenia (Oravecz et al., 2007), Japan (Nakaji et al., 2004), China, Hong Kong, and Taiwan (T. P. Ho et al., 1997). On the contrary, reciprocal suicide peaks were observed in summer months in countries located in the Southern Hemisphere, such as Australia (Cantor et al., 2000; Lambert et al., 2003; Rock et al., 2003; Law & De Leo, 2013), Chile (Retamal C & Humphreys, 1998; Heerlein et al., 2006), and South Africa (Flisher et al., 1997).

In addition to this seasonality focus, more recent research has focused on whether weather conditions and suicide are correlated in individual time series for certain locations, such as temperature, precipitation, sunlight duration, thunderstorms, atmosphere pressure, solar radiance, and air pollution. The answer to this question has been inconclusive in different regions.

The impact of precipitation differs across locations, especially in places with extreme weather conditions, such as drought areas and tropical areas. For example, increasing precipitation reduces suicide rates in drought areas (Nicholls et al., 2006; Hanigan et al., 2012) but raises suicide rates in tropical and subtropical areas (Tsai, 2010).

Precipitation is negatively associated with suicide rate of the general population in New South Wales (Nicholls et al., 2006), a state in Australia, which was declared to be more than 98% in drought during 2018 and 2019. A decrease in precipitation of about 300 mm would lead to an increase in the suicide rate of approximately 8% of the long-term mean suicide rate, which supports a long-held assumption that drought in Australia increases the likelihood of suicide.

Based on Nicholls et al.'s work, Hanigan et al. (2012) conducted a more complex analysis to explore the relationship between drought and suicide of the rural population in New South Wales. Instead of using actual precipitation levels, they used a previously established climatic drought index as a predictor of suicide among males and females, respectively. The relative risk of suicide for rural males aged 30-49 years raised with increased values of the drought index. In contrast, the risk of suicide for rural females aged greater than 30 years declined with increased values of the drought index.

In contrast, in the areas with regular precipitation conditions, such as tropical or subtropical areas, increasing precipitation level raises the risk of depression and suicide. For example, the annual cumulative rainfall is positively associated with the suicide rate of the general population in Taiwan (Tsai, 2010).

Studies also found no statistically distinguishable effect of precipitation on suicide (Lambert et al., 2003; Ajdacic-Gross et al., 2007; Ruuhela et al., 2009; Carleton, 2017). Reasons for these discrepancies in results are likely due to the limited sample sizes, differences in regression methods, differences in baseline precipitation levels across locations, and/or difficulty in separating precipitation from other factors that covary with it. The varying results show further study is certainly warranted to identify precipitation as a causal factor in suicides.

Sunshine exposure may affect suicide risk through regulation of serotonin (Turecki et al., 1999), or melatonin levels (Stanley & Brown, 1988), but supportive empirical evidence is lacking. More recent studies evaluated the hypothesis that sunshine triggers suicide utilizing more reliable statistical approaches. Similar to precipitation, however, no consistent conclusion of the relationship between sunlight exposure and suicide of the general population has emerged.

A positive association between sunshine and suicide rates was found in twenty countries around the world, including Austria, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Japan, Mexico, Netherlands, Norway, Spain, Sweden, Switzerland, and the United States in the Northern Hemisphere, and Australia and New Zealand in the Southern Hemisphere (Petridou et al., 2002). Peak suicide incidence was found in May or June in countries located in the Northern Hemisphere. Reciprocally, November or December was the peak suicide months in the two countries in the Southern Hemisphere. Total sunshine is positively associated with the peak suicide months in the corresponding countries, which indicates that sunshine may have a triggering effect on suicide. Similar results were found in Belgium (Maes et al., 1994), United Kingdom (Salib & Gray, 1997), southern Australia (Lambert et al., 2003), Greece (Papadopoulos et al., 2005), and Chile (Heerlein et al., 2006).

Several studies, however, found sunlight exposure is negatively associated with suicide rates (Wehr & Rosenthal, 1989; Tietjen & Kripke, 1994; Preti et al., 2000; Ajdacic-Gross et al., 2007; A. C. Yang et al., 2011). For example, Wehr and Rosenthal (1989) found that higher suicide rates correspond to areas in Italy that are less exposed to sun. Preti (1998) reinforced this result, although the seasonal occurrence of suicides peak in sunny months in Italy. Tietjen and Kripke (1994) found that sunlight inhibits suicides in Sacramento, California, United States, but not in Los Angeles. The decrease in the significance of the weather effects on suicide is correlated with rising per capita gross domestic product. In addition, the authors argued that weather effects are minimized as urban people may simply spend very little time outdoors. Besides, female suicide relationships with climate indicators were found less significant than for males in Italy (Preti et al., 2000).

In addition, several meteorological variables showed a significant association with suicide rates or suicide risk, including thunderstorms on the preceding day of suicide occurrence, higher atmosphere pressure, high solar radiance (Deisenhammer et al., 2003; Papadopoulos et al., 2005), low humidity (Salib & Gray, 1997; Wehr & Rosenthal, 1989; Deisenhammer et al., 2003), and sunspot activity (A. C. Yang et al., 2011). Undoubtedly, predisposed individuals are more likely to develop suicidal ideation with the interaction of psychological and environmental influences that additionally contribute to the risk of suicide. The cutting-edge investigation for environmental risk factors associated with suicide has broadened beyond meteorological variables to include exposure to air pollutants. A transient increase in particulate matter is associated with higher suicide risk in South Korea, especially for individuals with preexisting cardiovascular disease (C. Kim et al., 2010). Studies conducted in Taiwan found a classic seasonal pattern of suicide in early summer associated with increased air particulates and decreases in barometric pressure. The latter is also correlated with increasing temperature. The risk of suicide increases in the long run as gaseous air pollutants increase, including sulfur dioxide and ozone (A. C. Yang et al., 2011). Bakian et al. (2015) found consistent positive associations between short-term exposure to nitrogen dioxide, particulate matter, and sulfur dioxide with suicide in Salt Lake County, Utah.

The most researched question regarding the relationship between suicide and weather conditions is whether temperature is associated with suicide. The answer has been inconclusive in different regions: positive in France (Souêtre et al., 1990), Canada (Marion et al., 1999), Austria (Deisenhammer et al., 2003), Taiwan (H. C. Lee et al., 2006), Switzerland (Ajdacic-Gross et al., 2007), England and Wales (Page et al., 2007), East Asia (South Korea, Japan, Taiwan) (Y. Kim et al., 2016), United States (P. G. Dixon et al., 2007), Finland (Ruuhela et al., 2009), India (Carleton, 2017), United States and Mexico (Burke et al., 2018); negative in Taiwan (Tsai, 2010); and no effect in California (Tietjen & Kripke, 1994), United States (P. G. Dixon et al., 2007),[2]and South Australia (Lambert et al., 2003).

Various reasons can explain these discrepancies in results: differences in sample sizes and research methodology. In addition, the baseline suicide rates and temperature are different across locations, where the cultural and economic conditions are also different. Although we consider temperature as a random variable, on average the temperature levels also exhibit seasonality at a certain location that may potentially be correlated with the seasonality of suicide. Furthermore, numerous non-climatic factors of suicide may potentially co-vary with climatic variables. Thus, it is challenging to separate temperature as a causal effect of suicide from other time-varying confounds.

[2]Regressions in this study applied data in five counties in the U.S., including Orange County, New York; Pierce County, Washington; Richland County, South Carolina; Sedgwick County, Kansas; and Ventura County, California.

2.3 Farmer suicide

There is considerable worldwide interest in better understanding the manifold factors contributing to farmer suicide rates since the prevalence of mental health disorders and suicide amongst agricultural producers is a global issue. For example, farmers in Australia, a country traditionally associated with agricultural production, presented from about 1.5 to 2 times higher suicide rates compared to the national average (Arnautovska, McPhedran, & De Leo, 2014). The farmer suicide rate is also high in France, at about 40 per 100,000 farmers per year. According to a survey conducted by the French national public health agency, one French farmer commits suicide every two days (Michalopoulos, 2018). France's public health institute published statistics in 2016, reporting 985 farmers killed themselves from 2007 to 2011. The farmer suicide rate is 22 percent higher than that of the general population (Rougerie, 2017). In the United States, suicide rate of male agricultural managers was at nearly twice the rate of men in the general population in 2016 (Peterson et al., 2018). Two thirds of producers reported anxiety disorders, and over half reported depression in the Midwest (Rudolphi et al., 2020). In the United Kingdom, farmers account for the largest numbers of suicides amongst any single occupational group (Gregoire, 2002). In New Zealand, people working in farming, fisheries, or forestry and trades had higher suicide rates than people in other occupations. In contrast, people working in offices and homemakers had the lowest suicide rates (Gallagher et al., 2008). In addition, suicide rates of farmers were found to be elevated in many other countries, including India (Patel et al., 2012), Brazil (Meneghel et al., 2004), and Japan (Klingelschmidt et al., 2018).

Studies discussing cases of farmer suicide are reviewed in this section. Some of these studies focused on the relationship between farmer suicides and adverse conditions farmers face that reflect authors' speculation of the reason for farmer suicide, while others conducted case studies and surveys to perform basic analysis, such as summary statistics, to find patterns of farmer suicide. A few studies provided scientific evidence of factors correlating or causing farmer suicide using rigorous data analysis.

2.3.1 Non-U.S. studies

There is a rich body of literature in Europe that connects farmer suicides to various causes. Two publications summarized factors associated with the high rates of suicide among farmers in the United Kingdom, investigated by psychological autopsy, including but not limited to the following factors: (1) easy availability of firearms; (2) rural stress; (3) stress associated with work; (4) financial difficulties; (5) relationships (e.g. family) problems; (6) physical health; (7) stoic personality (Malmberg et al., 1997; Hawton, Simkin, et al., 1998).[3] In areas like England and Wales, rural life can be difficult for farmers due to a shortage of low-cost housing, lack of transportation, unemployment, and disappearance of local facilities. In the 1900s, farming life changed dramatically, such as intensively increased mechanization of farming. Farmers can be anxious about having to change farming methods and face financial problems with debt and changes in paperwork filing. At the same time, the development of technology has made farming a more isolated job. Farmers feel less involved in their communities. Other problems including long hours of work, inability to take breaks from work and unpredictability of the weather are some additional factors to farmer suicide. As

[3] Farmers are more likely to keep their problems to themselves. For example, in a small community it can be difficult to admit to financial problems without repercussions for the business(Malmberg et al., 1997). More than half of suicides were associated with the factor of not having a confidant, compared with less than 10% of non-suicides among farmers in England and Wales (Hawton, Simkin, et al., 1998).

the tradition in the U.S., European farmers mainly are self-employed in a family business. Family problems such as divorce and inter-generation disputes can have a devastating effect in many cases. The authors pointed out that the reasons to commit suicide are likely to be complex and not solely related to any single problem listed above, which indicates no statistically significant association.

Research has shown that many suicides are impulsive, which makes the easy accessibility of lethal methods crucial. For example, in 1989, modifications in the law covering the registration, ownership, and storage of shotguns led to a notable decrease in the use of shotguns as a means of suicide among farmers in England and Wales. Hanging, instead, became the principal suicide method during that time (Hawton, Fagg, et al., 1998). More recent studies found suicides among farmers in the U.K. are substantially more likely to involve firearms (usually shotguns (N. Booth et al., 2000)) than suicides in the general population. This finding has been robust to different research methodologies, including case studies and surveys (N. Booth et al., 2000), observational data statistics (Hawton, Fagg, et al., 1998), and multiple regressions (Stark et al., 2006).

Farmers in the U.K. with smaller holdings suffer more stress with fewer supports compared to farmers with larger holdings (Hawton, Simkin, et al., 1998). The analysis of data from the postal questionnaire showed that 92% of farmers who committed suicide had farms of less than 300 acres, compared with 70% of farmers in the group who did not commit suicide.

The presence of mental health problems is the most common factor of suicides in the U.K, which was found in 82% of farmer suicides in the U.K. (Gregoire, 2002). A postal survey analysis by (N. J. Booth & Lloyd, 2000) indicated high levels of occupational stress in farming families in the southwest of England, with elevated levels of anxiety and depression associated with health issues, family problems, coping with new legislation, the amount of paperwork, and media criticism.

Farmers in Australia were more likely to be older, male, married, suffering financial hardship, have lived in a rural area for longer, live more remotely and in an area of disadvantage (Brew et al., 2016). Farmer suicide studies in Australia are mainly non-empirical examinations, including interviews, case studies, surveys, and other qualitative analyses. For example, Bryant and Garnham (2014) conducted interviews and case studies and found that many farmers in Australia were experiencing financial hardship and economic hopelessness and attributed blame to excess supply in the wine industry generated by state policies, suspension of contracts, and delayed or non-payment for produce. Farmers felt ethical injustice, distress, and disappointment, which could lead to suicide. Another qualitative analysis indicated three major social factors of suicide as perceived by Australian farmers themselves: changing rural communities, community attitudes and stigma, and relationship issues (Perceval et al., 2018).

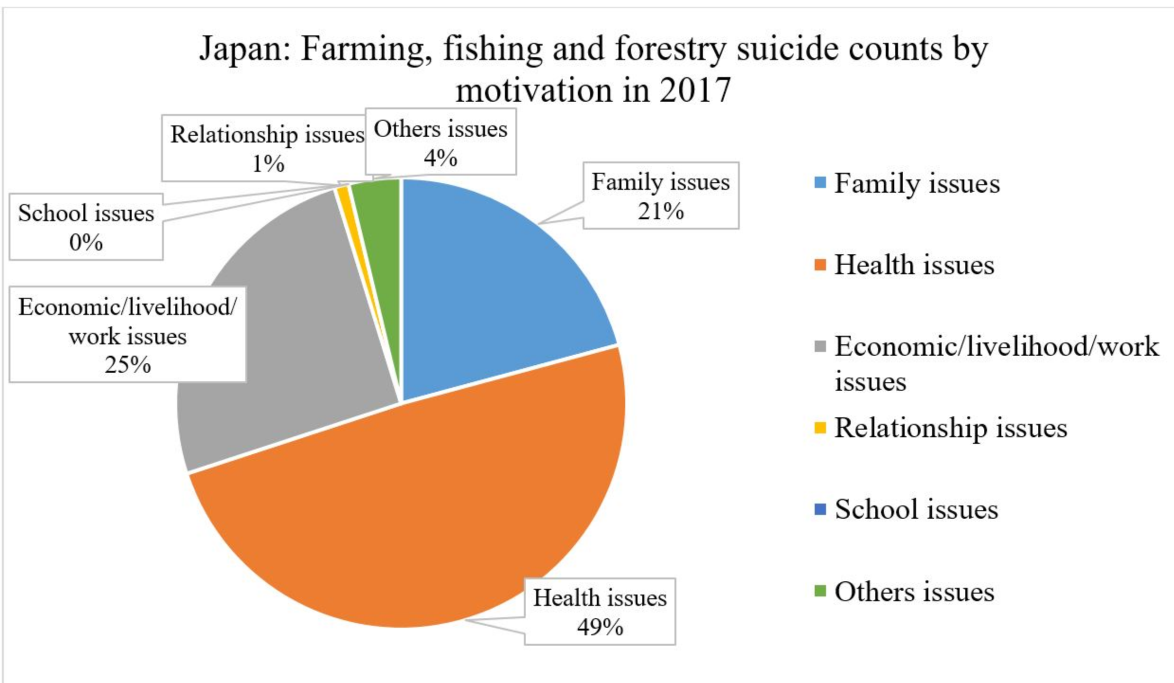
Although qualitative analyses provide insights into how farmers perceive the risk factors for suicide, it is hard to draw scientific inferences from interviews and surveys with limited sample sizes. In addition, participants' recruitment methods are likely to cause selection bias. Consistency of the interview schedule content and delivery is another factor that needs to control for. Regardless, the results of qualitative analyses can still be a valid reference as they provide subjective aspects of why farmers commit suicide.

Arnautovska et al. (2014) criticized treating farmer suicide as a homogeneous phenomenon and hypothesized that farmer suicide is higher in regions with higher proportions of farmers. However, they failed to find any significant association between farmer suicide rates and the proportion of farmers using Poisson regression on count data, regardless of the incidence and rates of suicide in farmers vary substantially across different regions of Queensland, a jurisdiction with one of the highest number of farmers in Australia. Furthermore, the authors questioned if the regional heterogeneity in farmer suicide is a reflection of general suicide rates in the same regions since large regional disparities in suicide rates among the general population have also been observed in Australia. Furthermore, the authors questioned if the regional heterogeneity in farmer suicide is a reflection of general suicide rates in the same regions since large regional disparities in suicide rates among the general population have also been observed in Australia. They expected farmer and non-farmer suicide rates would be positively associated with one another. However, no such association was found, which is likely because their model ignores the region fixed effects that can absorb regional variations. In addition, the sample only included 147 farmer suicide cases. Thus, their finding of no evidence of statistically significant associations between farmer and non-farmer suicide rates remains controversial.

Remoteness, for instance, poor access to health care, was found to be the most significant factor in the mental health and well-being of farmers in another empirical study in Australia, which applied the Generalized Estimating Equations (GEE) analysis, ranking higher than factors such as financial strain (Brew et al., 2016). Policies and programs that improve access for farmers to mental health services should be implemented, recommended by the authors. Moreover, farmers were found to be reluctant to seek health care for physical and mental problems (Hossain et al., 2008). The authors suggested that programs that aim to address attitudinal barriers to seeking help for professional mental services should also be supported.

A case study of 53 suicide survivors conducted in South Africa identified several contextual factors of suicide, including poverty, low education, alcohol use, a sense of desperation, the absence of coping mechanisms, easy access to pesticides as a means of self-harm, childhood within dysfunctional family environments, and interpersonal conflicts and violence (Holtman et al., 2011).

Figure 8: Japan: Farming, fishing and forestry suicide counts by motivation in 2007



Source: Japan Ministry of Health, Labour and Welfare, 2017

The elevated suicide rate among farmers is a noteworthy issue in Japan, as well. Japan's Ministry of Health, Labour and Welfare published statistics on the reasons or motivations of suicide based on the decedent's wills and police records of the suicide investigation by occupational group (Japan Ministry of Health, Labour and Welfare, 2017). Figure 8 shows the distribution of suicide motivations among people working in farming, fishing, and forestry industries in 2007.

Almost half of the agricultural workers who committed suicide did so due to health issues such as worries of disease, clinical depression and other body and mental diseases. A quarter of suicides were motivated by economic, livelihood or work issues, such as failure of work, bankruptcy, business slump, unemployment, the hardship of debt collection, liabilities, etc. Family issues were the next highest motivation for suicides such as the issues of parent-child and spousal relationships.

Farmers' well-being is well studied in India, especially cotton farmers. India is by far the world's largest cotton planter but its cotton sector is one of the world's most troubled, ranking 70th in yields and infamous for farmer suicide. Cotton farmers' suicide is a heated discussed topic in India. There are many non-empirical analyses that explore the reasons for cotton farmers' high suicide rate by summarizing the death data in cotton-growing states in the southeastern coastal region of India, such as Andhra Pradesh. Articles (Parthasarathy & Shameem, 1998; Revthi, 1998; Deshpande, 2002) speculated the following interrelated causes of cotton farmers' suicide: (1) adverse rainfall and low yields; (2) adverse (inconsistent) price, which suggests lack of integration of the markets for cotton across states, centres and regions; (3) rise in cost of cotton cultivation and particularly cash components of costs; (4) lack of knowledge of seeds and pesticides selection;[4] (5) bad position of co-operative credit agencies and commercial banks (lack of accessibility of institutional credit drives the farmers to depend excessively on moneylenders); (6) growing power of moneylenders, traders, and landlords; (7) growth of lease holding in cotton; (8) lack and failure of irrigation (near

[4]There are sixty varieties of cotton seeds available in the market. The majority of farmers lack of knowledge of which seed is suitable for their land and weather conditions. The adulteration of pesticides worsens the situation. Farmers arbitrarily used 10 to 12 varieties of pesticide. As a result, the cost of cultivation increases up to 1.5 times (Srivastava & Patel, 1990; Parthasarathy & Shameem, 1998).

drought conditions); (9) pest problems; and (10) deteriorating soil structure. These factors cumulatively lead to crop failure which is the root cause of farmer suicide. In addition, Durkheim's famous monograph on suicide is often invoked, indicating growing alienation of individuals from family, society and religion as the factors responsible for suicides. The unprecedented number of Indian cotton farmer suicides could be a typical example of the deepening alienation of individual from society and social disintegration.[5]

Bacillus thuringiensis (Bt) cotton is at the centre of a number of controversies, including the accusation of Bt cotton being responsible for an alleged increase in farmer suicide in India. Government agencies and seed companies believe the implementation of hybrid BT cotton has been successful, yet the cotton yields remain at low levels and production costs have risen 2.5-3 times.

Green revolution non-supporters argue that the technology package of the Green Revolution causes severe salination of the soil, indiscriminate exploitation and choking of the aquifer, and intense pollution with all types of pesticides. Multiple news speculated that transgenic cotton technology is the ultimate reason for high suicide rates in the main cotton-producing regions in India. For example, Nadal (2007) pointed out that Monsanto's Bt cotton variety only offers protection against cotton bollworm but not against other pests, which is still costly for farmers to keep looking for pesticides, for example, Spodoptera. The current genetic modification Bt technology adds costs to cotton without commensurate increases in yield. Prince Charles said in his 2008 pronouncement in New Delhi that he blames

[5]Social integration is measured by the number and strength of a person's social relationships with others. According to Durkheim, suicides indicate social disintegration. The more family ties binding the individual to the domestic group, the greater his social integration and the less likely he is to commit suicide. The situation of a homogeneous religious community, unified and integrated by uniform belief and standardised ritual is less likely to result in suicides (Parthasarathy & Shameem, 1998).

GM crops for farmer suicides and much of the world agrees with him (Herring & Rao, 2012).

Such speculation has been supported by some empirical studies. Annual suicide rates in rainfed areas are inversely associated with farm size, and yield, and positively associated with Bt cotton adoption (Gutierrez et al., 2015). Kranthi and Stone (2020) conducted long-term comparisons of Bt cotton with yields and other inputs at both countrywide and state-specific scales based on data over 20 years and concluded that Bt cottony yield increase is insufficient, although the initial reductions in pesticide use for one major cotton pest are significant. However, with Bt resistance in one pest and surging populations of non-target pests, farmers spend more on pesticides today than before the introduction of Bt and the situation will continue to deteriorate. Figures in peer-reviewed literature (Morse, Bennett, & Ismael, 2007) and studies by NGOs (Quyum & Sakkhari, 2005) also show evidence of Bt cotton increasing pesticide uses.

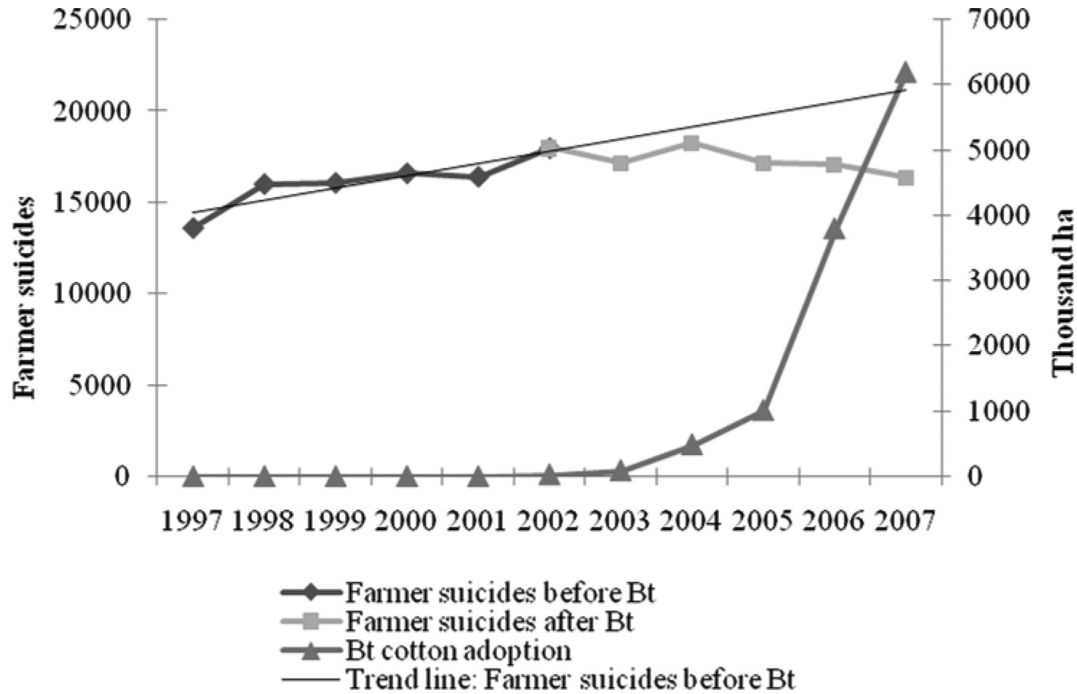
Using theoretically based and weather-driven, physiologically-based demographic models (PBDMs) and multiple linear regressions, Gutierrez et al. (2020) captured the age-stage mass dynamics of rainfed and irrigated cotton growth and the interactions with pink bollworm across five south-central Indian states and identified the association between hybrid cotton system and low yield, and farmer suicides. In contrast, non-GM cotton was found to double the rainfed cotton yield, reduce costs, and decrease insecticide use, which should be a viable solution for Indian cotton farmers in rainfed and irrigated cotton areas of the same five states to ameliorate suicides.

Many scholars criticized the accusation of Bt cotton as one of the factors of farmer suicide in India. Studies found the net returns from Bt cotton farming across 22 field studies covering 12,931 farming plots increased by 53.5% as a weighted average in comparison with non-Bt fields. Such increases can be decomposed into a weighted average of 34.4% decrease in pesticide use, leading to a 45.8% decrease in pesticide cost and a 39.1% increase in yields. Indeed, as the Bt opponents argued, the total cost of cultivation increased by an average of 15%, but increased costs were more than compensated by better yields, resulting in higher net income for farmers (Gruère & Sengupta, 2008). Many peer-reviewed studies have supported the finding that insecticide use dropped with Bt cotton adoption (R. M. Bennett et al., 2004; R. Bennett et al., 2005, 2006; Qaim, 2003; Qaim et al., 2006). Based on the result of a five-year field study comparing field-level and farm-level impacts before and after Bt cotton adoption from 2003 t0 2007, insecticide sprayings are found reduced by 54.7%, although predation by non-target pests was rising. Cotton yields were boosted 18% across the sample villages, with greater increases among poor farmers with the least access to information. Bt cotton adoption has been proven successful in the Warangal District of Andhra Pradesh, India (Stone, 2011).

Interestingly, studies revealed the suicide rate for male Indian farmers is slightly lower than for non-farmers (Plewis, 2014). The pattern of changes in suicide rates from 1996 to 2011 is consistent with a beneficial effect of Bt cotton, although not in every cotton-growing state. Farmer suicide, in terms of count, was not observed in correspondence to national Bt cotton adoption (Gruère & Sengupta, 2011). Figure 9, reproduced from Gruère and Sengupta (2011)'s article, compares the trend in the number of farmer suicide at the national level between 1997 and 2006 in India with the spread of Bt cotton in the country. There was a clear reduction in annual growth in farmer suicides after the introduction of Bt cotton in 2002.

Note that the farmer suicide occurrence in this figure does not represent the actual

Figure 9: Farmer suicides and Bt cotton area in India, 1997–2007.



Source: National Crime Records Bureau (NCRB) of the Ministry of Home Affairs, India

share of farmers committing suicide who cultivated cotton, let alone Bt cotton, and among them who committed suicide because of Bt cotton crop failure. This figure only provides an alternative assessment of the evidence at the aggregate level. Nonetheless, it still delivers the idea that accusing Bt cotton of causing the increase in farmer suicide in India merely based on information and data collected from published reports, journal articles, media news, magazine articles, and radio broadcasts is not a sufficient, nor a necessary statement. Moreover, Bt cotton technology has been proved by multiple empirical studies to be a success story in India, with farmers benefiting from pesticide reductions, higher effective yields, and significantly higher profits (Qaim et al., 2006; Sadashivappa & Qaim, 2009).

Not only do studies indicate Bt technology adoption is successful in India, but it has also been found prosperous in other cotton-growing countries, such as Pakistan. The first generation of Bt gene cotton was introduced to Pakistan in 2002 and the cultivation of Bt cotton varieties has rapidly increased since 2005. Almost 60 percent of the cotton area was under Bt varieties in 2007. The economic performance of Bt cotton in Pakistan was examined by Nazli et al. (2010) based on data collected from a structured questionnaire survey in 2009 in two districts, i.e., Bahawalpur and Mirpur Khas. Results show a reduction in the number of bollworm sprays, which leads to a decrease in pesticides expenditures and total pesticide control costs (including bollworms and non-bollworm pests). Total production costs decreased in Bahawalpur but increased in Mirpur Khas. Correspondingly, the yield gain was higher in Mirpur Khas, compared to the other district, Bahawalpur, which results in more total revenue and gross margins gain in Mirpur Khas than in Bahawalpur.

Based on data from 147 studies around the world, Klümper and Qaim (2014) carried out a meta-regression analysis of agronomic and economic impacts of GM crops including cotton, soybean, and corn on crop yields, pesticide use, and farmer profits to consolidate the evidence that GM crops benefit farmers in both developed and developing countries. On average, GM technology adoption has reduced chemical pesticide use by 37%, increased crop yields by 22%, and increased farmer profits by 68%. Yield gains and pesticide reductions are larger for insect-resistant crops than for herbicide-tolerant crops. Yield and profit gains are higher in developing countries than in developed countries. Such evidence helps to gradually increase public trust in GM technology.

Other than GM technology, one of the most discussed factors that be blamed for causing farmer suicide in India, scholars explored other factors by conducting rigorous empirical analyses to provide quantitative evidence, including indebtedness (Mishra, 2006; Gedela & Prakasa, 2008; J. Kennedy & King, 2014; Bhise & Behere, 2016), poverty (Hebous &

Klonner, 2014), value of produce (Mishra, 2006; Gedela & Prakasa, 2008; J. Kennedy & King, 2014) and environmental factors such as ground water storage (Chinnasamy, Hsu, & Agoramoorthy, 2019) and rainfall rate (Harita et al., 2020).

Increasing indebtedness and decreasing value of products, especially cash crops and livestock, are the two common factors identified by empirical studies that contributed to farmer suicide in India. Gedela and Prakasa (2008) practiced logistic regression modeling the probability of a farm household committing suicide as a function of seven relative risk factors including the value of livestock in rupees, family size, outstanding debt in rupees, the value of agricultural produce in rupees, outstanding debt per hector in rupees, the value of produce per hector in rupees and literacy levels as a binary variable. Results indicated that if the value of livestock and value of produce increase by 1000 rupees each, then the odds that a household is one with a suicide victim decrease by 69% and 95% respectively. If the amount of outstanding debt per hectare increases by 1000 rupees, the odds that the household is one with suicide victim increases by 2%. If the respondent is illiterate then the odds that the household is one with suicide victim increases by 47%. Similarly, another step-wise logistic regression analysis suggested that if the outstanding debt of an Indian farm household increases by 1000 rupees then the odds that the household is one with a suicide victim increase by 6%. In addition, if the household owns bullocks then the odds that it is a household with a suicide victim decreases by 65% (Mishra, 2006).

Using district-level data on farmer suicides in two major states in India from 1998 to 2004, Hebous and Klonner (2014) elicited the causal effect of transitory economic shocks on suicide using rainfall conditions as an instrumental variable based on the linkage between lack of rainfall and poverty transitory spikes, and concluded that a one percent increase in poverty drives up male farmer suicide rate by 0.57% and decreases female farmer suicide rate by 1.05%. The combined causal effect of a poverty shock on suicides in farm households is positive given that suicides among male farmers are four times as frequent as among females on average. In addition, a shift in cropping patterns from subsistence to cash crops, especially cotton, tends to reduce male suicides. Based on the linear regression of the state-level suicide rates of farmers in India from 2001 to 2005, J. Kennedy and King (2014) identified a significant positive relationship between suicide rates and (i) the percentage of marginal farmers, defined as farmers with landholdings of less than one hectare, (ii) cash crops, such as coffee and cotton, and (iii) indebtedness. Specifically, If the proportion of marginal farmers, cash crops, or indebted farmers increases by one percent, the suicide rate (per 100,000 per year) of farmers will rise by 0.437, 0.518, or 0.549, respectively, holding all other variables constant.

Bhise and Behere (2016) applied both psychological autopsy and statistical analysis including univariate analysis through Mantel-Haenszel estimate of odds ratio and multivariate conditional logistic regression analysis model with a forward stepwise procedure to assess the association of various individual risk factors of farmer suicides. Results show that being indebted in the last five years increases the risk of suicide by nearly four times. The presence of a diagnosable psychiatric illness and the presence of stressful life events in the preceding year were also significant factors increasing the odds of committing suicide.

Counter-intuitively, various studies suggest that farmer suicides in India have increased since the modernization of the Indian economy (Mohanakumar & Sharma, 2006; Sridhar, 2006; Mitra & Shroff, 2007; Jeromi, 2007; Sadanandan, 2014; Arya et al., 2018). For instance, Arya et al. (2018) specified a series of negative binomial regression models and found that populations residing in less economically developed states were associated with lower suicide risk compared to more economically developed states. Populations with higher agricultural employment were associated with higher suicide risk compared to populations residing in states with lower agricultural employment. States with the lowest levels of literacy were associated with a lower risk of suicide. States with lower proportions of the population with Hindu religion were associated with a lower risk of suicide.

2.3.2 Studies in the U.S.

There have been newspaper reports, studies with a summary of peer-reviewed studies, and data summary statistics studies showing various potential factors that may lead farmers to be at higher risk of suicide than other occupational groups in the U.S. In particular, the rapidly evolving economic environment in agriculture (U.S. Bureau of the Census , 1986), declining farm economy (Ragland & Berman, 1991), the hazardous work environment supported by a high rate of injuries and other illnesses (Cordes & Foster, 1988), the isolation of rural lifestyle (Hoffman & Lamprey, 1979; Tiesman et al., 2015), the lack of access to emergency medical care (Mutel & Donham, 1983) and mental health services in rural areas (Hoffman & Lamprey, 1979), easy access to firearms (Stallones, 1990; Stallones, Doenges, & Dik, 2013), financial stress (Platt, 1984; Eisner, 1992; Scheyett, Bayakly, & Whitaker, 2019; Reed & Claunch, 2020), longer work hours for older farmers than other occupational groups that leads to higher rate of getting chronic diseases and lower mental health state than the general population (Lizer & Petrea, 2007), and pesticide/chemical exposure (E. Lee et al., 2002; Reed & Claunch, 2020).

Although there have been non-regression studies of suicide among farmers and agricultural workers, there have been few systematic studies assessing the statistically significant correlations or causal relationship between farmer suicide and its factors. A few of the above-mentioned potential factors were supported by rigorous regression analysis.

A. Kennedy et al. (2021) obtained suicide records data across 40 states of the U.S. between 2003 and 2016, including 2801 cases of "farming-related" suicide decedents. Results from binary logistic regression of demographics of suicide decedents and circumstances of suicide revealed being in age groups of 55 years or older increases significantly increases the likelihood of the deceased individual being a farmer than a non-farmer. Similarly, a high likelihood of being a farmer who committed suicide versus a non-farmer is significantly and positively associated with being White, non-Hispanic, American Indian/Alaska Native, and having 8th grade or less education. Demographic characteristics with a negative association with being a farmer include being African American, having an associate's degree or higher, and having current or former military service. In terms of suicide methods, using a firearm is associated with higher odds of being a farmer than a non-farmer. Hanging, strangulation, asphyxiation, dying by a sharp object and jumping or vehicular impacts were found less likely to be used by farmers compared to a firearm.

Bjornestad et al. (2021) conducted a mail survey of 4,000 producers who either conducted farming activities on at least 1000 acres or who owned a dairy farm purchased in Kansas, Michigan, Missouri, or South Dakota. The authors utilized linear regression analysis of 600 responses to explain the variation in a self-reported suicide risk score, SBQ-R, which assesses four different aspects of suicidality, by 27 various independent variables. Only one independent variable showed significant association with the natural log-transformed suicide risk score, namely coping through self-blame. A one-unit increase in self-blame is associated with an increase of 6.7% in the suicide risk score, holding all other conditions constant.

2.4 Summary

In summary, factors associated with suicide among the general population have been extensively studied for hundreds of years. Most of the research assessed the correlation between suicide and economic, demographic, household-related, and health factors. It is challenging to infer a causal relationship from these factors because it is nearly impossible to know if the model has exhausted all relevant factors. Assuming weather events are random variables, considerable studies explain variations in suicide among the general population by various climatic conditions, such as temperature, precipitation, sunlight exposure/duration, and air pollution. However, the weather effect can be heterogeneous across occupations, especially for people working in the farming industry.

Although the existing literature examining whether weather conditions and suicide are correlated has been inconclusive and controversial, the effect of weather on farmers is pronounced relative to the general population because farmers spend significant amounts of time outdoors. Moreover, farmers' livelihoods highly depend on weather conditions.

For example, Burke et al. (2018) argued that suicides in the general population respond strongly and linearly to variation in temperature: suicide rates rise 0.7% in US counties and 2.1% in Mexican municipalities for each 1°C increase in monthly average temperature. Such temperature effect describes one of the triggers of peoples' ideation or action of committing suicide. However, for farmers, the weather effect is more than just a trigger to suicide. It is an underlying cause of reductions and increased volatility in farm incomes. Increasing temperatures may damage crops and reduce yields. In addition, the average temperature effect for the general population might underestimate the impact for the subgroup of agricultural workers due to the strong association between temperature and crop yield, which closely affects farmer's income. The temperature effect on suicide is heterogeneous. This study will address such heterogeneity particularly for farmers and explore the underlying mechanism of temperature on farmers' propensity to commit suicide.

Carleton (2017) demonstrates that fluctuations in climate, particularly temperature, significantly influence suicide rates in India: warming over the last 30 years has been responsible for 59,300 suicides, accounting for 6.8% of the total upward trend. She notes that more than three quarters of the world's suicides occur in developing countries and one fifth of the world's suicides occur in India. These statistics are potentially misleading since the suicide *rates* in developing countries are not necessarily higher than the rates in developed countries due to the large populations in key developing countries such as China and India.

Table 3: Suicide rates by World Health Organization region

WHO region	2016	2015	2010	2005	2000
Europe	15.4	15.7	17.9	20.7	21.8
Southeast Asia	13.2	13.3	13.5	14.2	14.3
Global	10.6	10.7	11.5	12.3	12.9
Western Pacific	10.2	10.2	11.7	12.2	13.1
Americas	9.8	9.9	9	8.5	8.3
Africa	7.4	7.4	7.6	7.9	8.3
Eastern Mediterranean	3.9	3.9	4.3	5.1	5.0

Note: rates are in per 100,000 population per year, ranked by 2016 rates.

Indeed more developed countries in general show higher suicide rates compared to developing countries. Table 3 shows that Europe has the highest suicide rates, compared to the other five regions defined by the World Health Organization (WHO), followed by

Southeast Asia (World Health Organization, 2018a), where South Korea has the 10th highest suicide rate of 20.2 per 100,000 (World Health Organization, 2018b).

In addition, Carleton finds that for temperatures above 20°C, each 1°C increase in a single day's temperature causes about 70 suicides among the general population, on average, during India's agricultural growing season. Even though Carleton recognizes the complicated weather effects on suicide, the 70 suicides for 1°C increase in temperature is still an average effect. The heterogeneity of weather effects on suicide is still poorly understood.

Further, the degree-day threshold Carlton chooses, i.e., 20°C, is arbitrary, although she shows robustness for the thresholds of 15°C, and 25°C. These threshold temperatures fall in the middle of the crop growing beneficial heat range, from 8°C to 32°C (Ritchie & Nesmith, 1991; Schlenker & Roberts, 2009), raising the question of why temperatures in these ranges should be associated with increases in suicide.

Regarding suicide among farmers, in particular, there are extensive studies in countries with high farmer suicides historically, such as India. Even though reasons for farmer suicide vary by country, economic and work-related issues are the common factors that cause farmers to commit suicide, which echos our point that there must be something unique about this occupation that makes farmers so vulnerable to suicide.

Empirical studies on farmer suicide in the U.S. are especially limited, particularly the causal inference papers. Two recent papers are summarized in the previous subsection that assessed characteristics of suicide among people working in the farm industry in general and producers' self-reported suicide risk factors. The former fit individual-level suicide records data over 13 years as cross-sectional data to fit the logistic model, which ignores the time-varying factors and potential time trends. These omitted variables are likely to be correlated with the demographic variables and economic variables in the model, which potentially result in an endogeneity problem. The latter paper used limited data from a questionnaire that may suffer from selection bias since the producers who decided to respond to the survey are likely to be more extroverted or responsive, which could affect how they evaluate their self-reported suicide risk scores.

The heterogeneity of existing studies and paucity of scientific evaluation proscribes firm conclusions related to causal factors of farmer suicide in the U.S. There is no literature, as far as I know, that addresses the determinants of farmer suicide in the U.S. utilizing rigorous empirical analysis. This review demonstrates that there is a great need for a stronger and broader evidence base in the field of farmer mental health wellness. This study seeks to fill this gap in the literature, while acknowledging that suicide is a complex phenomenon with many interacting social, environmental, and biological causal factors.

3 Theoretical Model

Consider a model of a farmer choosing between hours of work and leisure to maximize utility, where we assume that i) weather, e.g., temperature and precipitation, is an exogenous factor in determining yield, ii) consistent with prior literature, yield is a nonlinear function of weather (Schlenker & Roberts, 2009) and inputs such as water and fertilizer, and iii) farmers are price takers in both input and output markets.

The profit function of a farmer is represented by

$$\pi = pQ - \mathbf{p_z z} - F, \tag{1}$$

where p and $\mathbf{p_z}$ represent the output and input price (vector) respectively. F is fixed cost associated with fixed inputs $\mathbf{k}$. Q, the output quantity, is a nonlinear function of farm operator's work time, w, devoted into both on-farm activities and management or operation activities; and other inputs $\mathbf{z}$, such as hired labor, water, and fertilizer, the fixed inputs, plus the exogenous factor, θ:

$$Q = f(w, \mathbf{z}, \mathbf{k}|\theta), \tag{2}$$

where θ represents the exogenous factors affecting production, such as precipitation, temperature, and other weather events.

Weather events affect yield of an agricultural product non-linearly. Beneficial weather increases yield and therefore increases profit. Harmful weather shocks reduce yield and decrease profit. The relationship between weather and yield could be explained by figure 10.

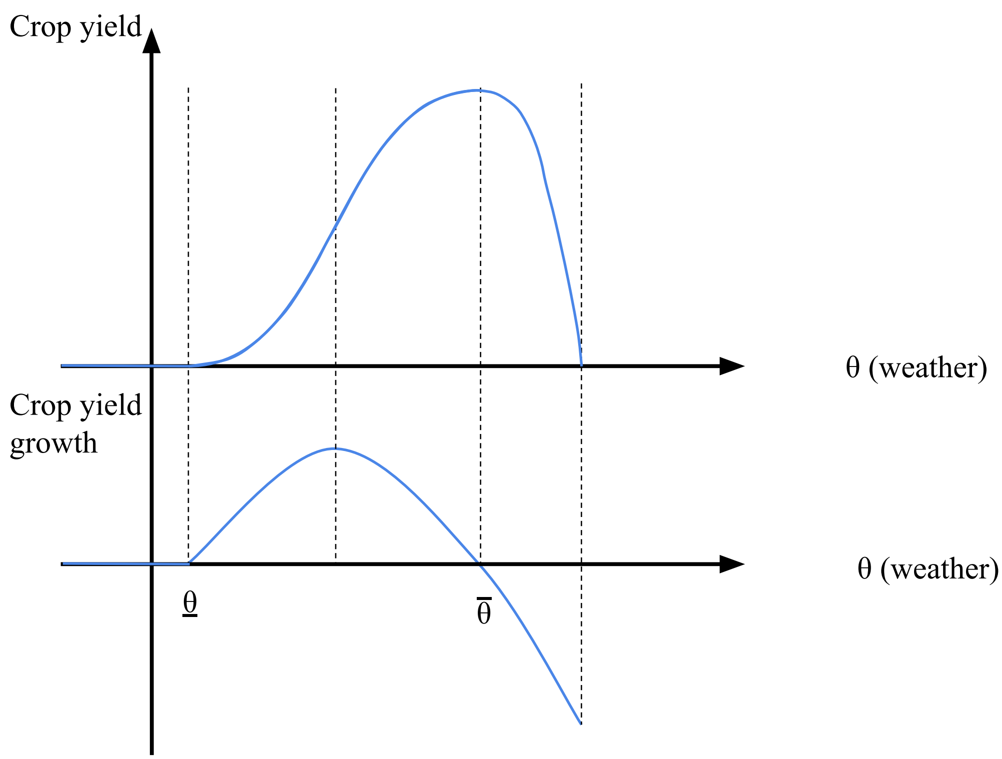


Figure 10: Yield and weather

When θ falls into the production beneficial range, i.e., $[\underline{\theta}, \bar{\theta}]$, yield increases. When the weather passes the level of $\bar{\theta}$, yield decreases.[6] The yield growth changes correspondingly in the bottom part of figure 10. For example, for corn, soybean and cotton, yield growth increases gradually with temperature up to 29-30°C, depending on the crop, and then decreases sharply (Schlenker & Roberts, 2009). In another example, grazing animals stop eating in extreme heat. Instead, they look for shady locations or rest at cool places which may end up in weight loss. Similarly, only some appropriate precipitation levels boost crop yield growth. Otherwise, values from two tails such as drought and flood both damage crop yield. Drought

[6]In reality, maybe certain inputs can offset the adverse effect of extreme temperature on yield function. For example, investing in genetic-modified plants with improved resistance to extreme cold or heat temperatures. For simplicity, the current model assumes $\frac{\partial Q}{\partial \theta}$ is not a function of other inputs, i.e., $\frac{\partial^2 Q}{\partial \theta \partial z} = 0$.

also reduces yields on pastures.

Assume weather, θ, follows a particular distribution with a probability density function $g(\theta)$ and cumulative density function $G(\theta)$. The probability of having beneficial weather is $Pr[\theta \in (\underline{\theta}, \bar{\theta})] = G(\bar{\theta}) - G(\underline{\theta})$. Conversely the probability of having harmful weather is $G(\underline{\theta}) + 1 - G(\bar{\theta})$.

A farmer chooses the level of consumption goods, x, as a component of utility, subject to an income constraint. Yield, thus, is a mechanism through which weather affects the farmer's utility. In addition, recall that health condition and family harmony level are two primary reasons or motivations of suicide for agriculture workers (Japan Ministry of Health, Labour and Welfare, 2017). Thus, we express utility as a function of consumption of goods, x, and also variables representing farmers' utility from leisure and family activities, and physical and mental health:

$$U(x, V(l, w)), \tag{3}$$

where $V(l, w) = L(l) + H(w)$. l represents leisure time and $L(l)$ represents utility from these activities, including time spent with family. $H(w)$ is utility associated with health. Farm work effort, w, is assumed to be negatively associated with health level. Work hours and leisure hours are determined by a total time constraint, $T : w + l \leq T$. The more time spent farming implies a commensurate reduction in time spent on leisure and family activities. Similarly, more effort spent working has an adverse impact on health (Lizer & Petrea, 2007), and, thus, $\frac{\partial V}{\partial l} > 0$, $\frac{\partial V}{\partial w} < 0$.

3.1 A single-period model

Assume for simplicity that weather has a two-point distribution, good weather, θ_H, which yields some positive profit π_H with probability ρ, and a bad weather shock, θ_L, with probability $1-\rho$, which yields $\pi_L < 0$. We also assume for simplicity that farmers observe the realization of the random weather shock before applying variable inputs w and $\mathbf{z}$.[7]

Given a weather shock, $\theta_i, i = H, L$, a farmer maximizes her utility subject to the income and time constraint given a initial wealth or outside income, W_o. Here we consider z as a variable input scalar.

$$\begin{aligned} \max_{x,w,l,z} U(x, V(l,w)) \quad & \text{subject to} \\ & p_x x \leq pQ(w, z, \mathbf{k}; \theta_i) - p_z z - F + W_o \\ & \text{and} \quad w + l \leq T \end{aligned} \tag{4}$$

Given the single-period setting, we know farmers will spend all available income on consumption to maximize utility, i.e., the budget constraint is binding when there is a positive return in utility from consumption goods. Thus, $x^* = \frac{\pi_i + W_0}{p_x} = \frac{pf(w,z,\mathbf{k}) - p_z z - F + W_0}{p_x}$. Similarly, the time constraint also binds. We have $l = T - w$.

Normalizing the farm output price to 1, the utility maximization problem yields the following two first order conditions:

$$p_z = \frac{\partial(Q|\theta_i)}{\partial z} \tag{5}$$

[7] The alternative assumption is that farmers must make input decisions before observing θ. This puts the model in the world of expected utility maximization. The reality probably lies somewhere between these two polar cases, i.e., farmers commit some inputs, e.g., at planting time, before observing θ, but other inputs, e.g., associated with harvesting, would be determined after the realization of θ.

$$\frac{\partial U}{\partial V}\frac{\mathrm{d}V}{\mathrm{d}l} + \frac{\partial U}{\partial V}\frac{\mathrm{d}V}{\mathrm{d}w} = -\frac{\frac{\partial U}{\partial x}}{p_x}\frac{\partial(Q|\theta_i)}{\partial w} \tag{6}$$

Equation (5) is the standard condition for optimization of a variable input, i.e., the farmer chooses the variable input level so that the point where the marginal cost, i.e., the price of the input, equals its marginal revenue product.

We know that $\frac{\partial U}{\partial V} > 0$ and $\frac{\mathrm{d}V}{\mathrm{d}l} > 0$, thus, $\frac{\partial U}{\partial V}\frac{\partial V}{\partial l} > 0$. Similarly, $\frac{\partial U}{\partial V} > 0$ and $\frac{\mathrm{d}V}{\mathrm{d}w} < 0$, imply that $\frac{\partial U}{\partial V}\frac{\partial V}{\partial w} < 0$. Intuitively, these two terms represent the marginal loss of utility through leisure/family and health when a farmer invests more effort in working.

$\frac{\partial U}{\partial x}$ is the gain of utility from consuming one more unit of the consumption good. $\frac{\frac{\partial U}{\partial x}}{p_x}$ is the marginal utility per dollar that the farmer spends on the consumption good. $\frac{\partial Q}{\partial w}$ represents the marginal gain in profit of a farmer investing more effort in farming. Thus, $\frac{\frac{\partial U}{\partial x}}{p_x}\frac{\partial(Q|\theta_i)}{\partial w}$ gives us the marginal gain in utility through consumption goods by relaxing the income constraint.

Equation (6) explicates the trade-off in utility from increasing work effort on the farm. The farmer gains utility from farm work by increasing the farm profit and loses utility from investing less effort in maintaining family relationships and adversely impacting health. Equation (6) intuitively demonstrates a balance point under maximization that the farmer will choose the working effort level and consumption level at the point when the gain in utility from increasing work effort is equal to the loss in utility through less leisure and family harmony and worse health as the result of expanding work, given the weather realization.

Given a bad weather shock, a farmer could rationally work more, so as to minimize the damage to production loss and farm income from the bad weather shock. Consider a production function that is concave in w. A bad weather shock shifts down the production curve from $Q = f(w|\theta_H)$ to $Q = f(w|\theta_L)$. However, over a certain range for w, it is quite plausible that $\frac{\partial Q}{\partial w}|\theta_L > \frac{\partial Q}{\partial w}|\theta_H$. Figure 11 shows an example of when this scenario happens.

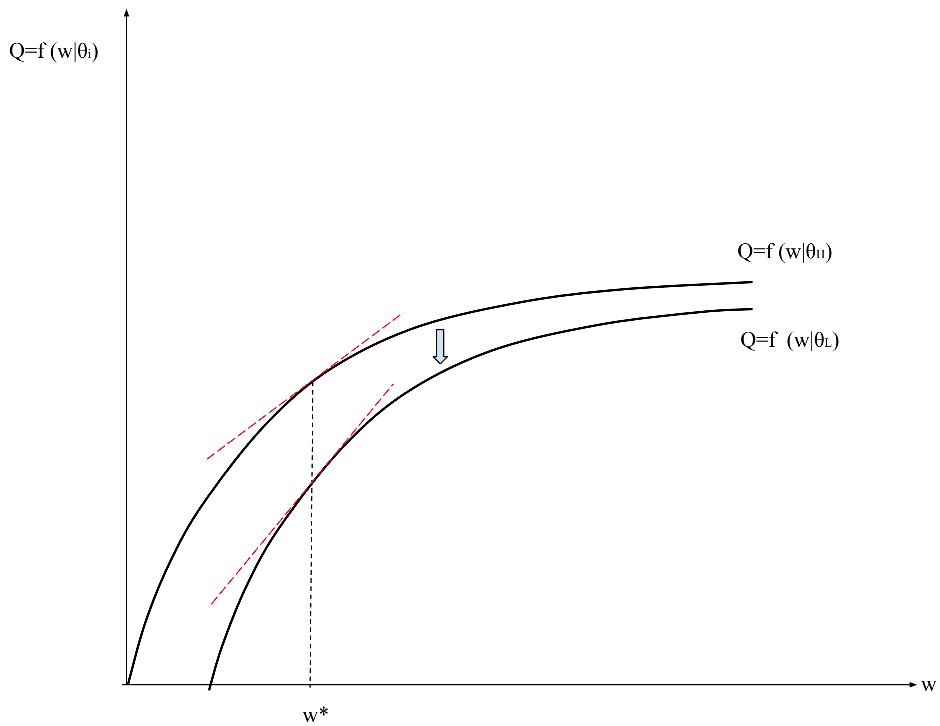


Figure 11: Weather shock and Production function

This rational response to an adverse weather shock also reduces utility from V compared to that for a good weather shock. Thus, even in the static model, a bad weather shock can have a "snowballing" effect that reduces farm income and also reduces utility from leisure and health through the work-leisure trade-off. Thus, it is possible to envision settings when severe adverse weather outcomes can so diminish a farmer's utility that it causes a spontaneous decision to commit suicide.

Impulsive suicide is a common concept in psychology. Yet for farmers, it could be a rare case since impulsive suicide is more common among young people (McGirr et al., 2008). Farmers in the U.S., however, are 57-58 years old on average (USDA NASS, 2017). Thus, although it is possible that a rational farmer chooses to commit suicide impulsively after a severe production loss, e.g., crop failure, such scenarios are likely to be rare.

More often, people who choose to take their own lives experience hardship, isolation, and hopelessness for a period of time, and commit what is known as planned suicide (Smith et al., 2008). Farmers encountering several years of drought or other weather-induced production failure or prolonged periods of low prices may face the prospect of bankruptcy or other severe financial pressures. These stresses can have a chronic impact on health and family relationships, making suicide emerge as a plausible outcome from feelings of hopelessness regarding the future. We explore these motivations in a generalized multi-period model in the next subsection.

3.2 Model with multiple periods

In this subsection, we start with a two-period setup, then extend the model to an N-period setting. For the two-period model, we consider a farmer who observes the weather in period $t = 1$ and forecasts the weather in period $t = 2$ conditional on the weather in period 1, rather than treating weather shock as an independent variable. Again, assume that weather, $\theta_{t,i}$, $i = H, L$, has a two-point distribution, a good weather shock θ_H with period 1 probability ρ_1, and a bad weather shock θ_L with probability $1 - \rho_1$. Also, θ_t is revealed in each period prior to input use being chosen.

A farmer has two streams of income in each period, π_t plus an exogenous income stream $W_t \geq 0$ in each period. Note that π_1 is deterministic once θ_1 is revealed, but π_2 is uncertain at time 1. The farmer consumes consumption goods, x_1 and x_2, in each period. She can also save money in the first period motivated by savings' impact on her utility in the second period. Denote saving as S, where $S = pQ_1(w_1, z_1, \mathbf{k}; \theta_{1,i}) - p_z z_1 - F + W_1 - p_x x_1$. We normalize the output price as 1 and omit fixed inputs in the production function for notation brevity hereafter. She earns interest γ on saving such that she is able to spend $S(1+\gamma)$ in addition to her income in the second period.

Conditional on the observed weather shock $\theta_{1,i}$, a farmer's perception of weather in period 2 has the following probability. $P(\theta_{2,H}|\theta_{1,i}) = \rho_2(\theta_{1,i})$ and $P(\theta_{2,L}|\theta_{1,i}) = 1 - \rho_2(\theta_{1,i})$. For example, if a farmer experiences a bad weather shock in period 1 and as a consequence believes the weather in period 2 is more likely to be bad, she considers $\rho_2(\theta_{1,L}) < \rho_1$ and $1 - \rho_2(\theta_{1,L}) > 1 - \rho_1$.

Having such belief of weather probability in mind at period 1, a farmer rationally anticipates how she will choose x_2, w_2, l_2 and z_2 to maximize her utility when period 2 arrives, given the observed weather $\theta_2 \in (\theta_H, \theta_L)$ and the saving level decided in period 1. She has the expected utility given her optimal choice of x_2^*, w_2^*, l_2^* and z_2^* as:

$$EU_2^* = \rho_2(\theta_1)U_H^*(x_2^*, v(w_2^*, l_2^*)) + (1 - \rho_2(\theta_1))U_L^*(x_2^*, V(w_2^*, l_2^*)).$$

The budget constraint in period 2 is binding, which implies that

$$x_{2,i}^* = \frac{Q_2(w_2^*, z_2^*|\theta_i) - p_z z_2^* + (1+\gamma)S + W_2}{p_x}, i = H, L$$

and $w_2^* + l_2^* = T$. Substituting x_2^* and l_2^* into the expected utility function, we find that the farmer's expected utility is a function of saving.

$$\begin{aligned} EU_2^*(S) = \rho_2(\theta_1)U_H^*\big(x_2^*(\theta_H, S), V(w_2^*(\theta_H, S), l_2^*(\theta_H, S))\big) \\ +(1-\rho_2(\theta_1))U_L^*\big(x_2^*(\theta_L, S), V(w_2^*(\theta_L, S), l_2^*(\theta_L, S))\big), \end{aligned} \tag{7}$$

where, based on the period 1 budget constraint, S could be replaced by $Q(z_1, w_1; \theta_1) - p_z z_1 - F + W_1 - p_x x_1$, thereby linking period 2 expected utility to period 1 choices.[8]

There is a channel through S whereby each of the variables chosen in period 1 impacts the utility in period 1 and also the expected utility in period 2 through x_2^*, z_2^* and w_2^*. The farmer identifies the marginal effect of savings in period 1 on period 2 consumption, health, and leisure and, hence, expected utility. Her expected utility in period 2 increases in general in S as it will typically true that $\frac{\partial U_{2.i}}{\partial x_2^*}\frac{\partial x_2^*}{\partial S} > 0$, $\frac{\partial U_{2,i}}{\partial V}\frac{\partial V}{\partial w_2^*}\frac{\partial w_2^*}{\partial S} > 0$, and $\frac{\partial U_{2,i}}{\partial V}\frac{\partial V}{\partial l_2^*}\frac{\partial l_2^*}{\partial S} > 0$.

The farmer recognizes in period 1 that she will make optimal choices in period 2, given S and the realization of θ_2. So the farmer can influence expected utility in period 2 through her saving in period 1, which is determined simultaneously with her period 1 consumption, work effort, and application of variable farm inputs.

She will choose S along with x_1, w_1, l_1, z_1 to maximize $U_1 + rEU_2^*$, where r is the

[8] To keep the compact style of equation, we will not show the equation with all the S inserted in equation (7).

farmer's personal discount factor.

$$
\begin{aligned}
\max_{x_1,w_1,l_1,z_1,S} \quad & U\big(x_1, V(w_1,l_1)\big) + r\rho_2(\theta_1)U_H^*\big(x_2^*(\theta_H,S), V(w_2^*(\theta_H,S), l_2^*(\theta_H,S))\big) \\
& + r(1-\rho_2(\theta_1))U_L^*\big(x_2^*(\theta_L,S), V(w_2^*(\theta_L,S), l_2^*(\theta_L,S))\big) \\
& \text{subject to} \quad p_x x_1 + S \leq Q(w_1, z_1; \theta_1) - p_z z_1 - F + W_1 \\
& \text{and} \quad w_1 + l_1 \leq T
\end{aligned}
\tag{8}
$$

Given the farmer maximizes her utility, she will exhaust all the available resources, i.e., time and money, to push her utility as high as possible. Thus, the two constraints are binding in equilibrium. We can rewrite x_1^* as $\frac{\pi_1^*(w_1^*, z_1^*; \theta_1) + W_1 - S^*}{p_x}$ and w_1^* as $T - l_1^*$. Intuitively, if a farmer has positive savings, she has to take into account how her current choices of x_1, w_1 and z_1 influence the amount of savings she has to carry forth into period 2 and then how the savings in period 2 impacts her discounted expected utility.

As a farmer spends one more dollar on consumption goods in period 1, she has one less dollar to save for period 2, which affects her expected utility in period 2. When she chooses x_1^*, she balances out the gain of spending one more dollar today on consumption goods and the discounted loss of having one less dollar saved for period 2. Similarly, when she decides the work effort, working one more hour today impacts the work-leisure trade-off but also impacts the saving due to $\frac{\partial S}{\partial Q_1}\frac{\partial Q_1}{\partial w_1}$ so that she takes the possible discounted gain in the future from working one more hour today into account. Analogously, $\frac{\partial S}{\partial Q_1}\frac{\partial Q_1}{\partial z_1}$ links period 1's decision of z_1^* to period 2's well-being. A farmer will choose the amount of farm variable input at the point where its marginal cost, i.e. its price, equals its marginal value product plus the possible discounted utility gain in period 2 through higher saving because of higher income.[9]

The saving decision also depends on other factors, such as the farmer's personal discount factor, interest rate and also her belief about the probability of future weather shock. For instance, when her discount factor is high relative to the interest rate, she is likely to reduce the amount of saving and vise versa. Her belief of $\rho_2(\theta_1)$ also influences the saving. If a farmer sees a high chance of getting better profit in the future, she is likely to save less in the current period.

With the understanding of how a farmer makes decisions in the current period, taking into account her belief of future utility, we are going to link such future expectations about utility to the concept of "hope." We define hope for the purposes of this study as how a person forecasts her future well being. A farmer has a high value of hope for the future when she believes her business will be successful, enabling human and monetary resources to be expended on utility-generating activities. In the opposite case, a farmer may feel hopeless and frustrated when she encounters severe difficulties in business, fails to successfully manage relationships and/or suffers from health issues. Hope or hopelessness can impact a suicide decision.

To quantify the hope of a farmer, we use equation (7), which describes how a farmer forecasts her own future utility given the observed weather shock in period 1. This is equivalent to how she forecasts period 2 utility in period 1. Denoting such hope function as $M(\cdot)$, we have:

$$M(\cdot) = rEU_2^*(S) = M(\rho_2, p_{x,2}, p_{z,2}, p_2, \gamma, r, W_2), \tag{9}$$

[9]The discussion here excludes the detailed derivative process and the FOC equations.

where $\rho_2, p_{x,2}$, and $p_{z,2}$ denote the farmer's subjective forecast of weather, consumption price and farm variable input price in period 2. Thus, hope is a function of perception of future weather conditional on the observation of current weather, input prices, price of consumption goods, the farmer's discount factor, and interest rate. In addition, output price, normalized to 1 in period 1 may change in period 2, making p_2 also an exogenous factor that influences a farmer's hope function, where p_2 is the farmer's subjective forecast of output price in period 2.

Following Hamermesh and Soss (1974), we assume that each individual has a taste for living, b_j, where $b_j \sim N(0, \sigma^2)$. Each farmer has a value of b_j that characterizes her subjective and latent preference for living. A farmer rationally commits suicide when the total discounted lifetime hope function plus taste-for-living parameter becomes non-positive, i.e., when

$$M_j(\rho_2, p_x, p_z, p, \gamma, r, W_2) + b_j \leq 0. \tag{10}$$

Farmer's belief of ρ_2 given θ_1 influences her hope function. Having a bad weather shock in period 1 could increase her subjective forecast about future bad-weather events, which decreases her hope. For those located at the left tail of the b_j distribution, even small negative shocks to the hope function can lead to a decision to commit suicide.

For example, if a bad weather shock in period 1 causes a farmer to forecast bad weather in period 2 (e.g., the farmer forecasts that the period 1 shock is due to climate change and, thus, likely to persist into period 2), she expects to receive $\pi_{2,L}$. In period 1, she might work more to minimize the damage to yield, as discussed in the static model. The "snowballing" effect created by bad weather shock reduces farm income but also decreases farmer's health and leisure through the work-leisure trade-off. In addition, although the farmer has the incentive to save money, her low profit in period 1 limits her ability to do so. And she sees no hope of getting better in period 2 with no saving, given her consumption level at period 2 is only $x_2^*(\theta_{2,L}) = \frac{\pi_{2,L}|\theta_{1,L}+W_2}{p_x}$. The expected bad weather in period 2 expands the "snowballing" effect of a bad outcome in period 1.

Holding other exogenous factors constant, a farmer's hope given a bad weather shock in period 1 could be very small and approaches zero, especially when she expects the weather shock in period 2 is also bad:

$$M_j(\rho_{2,H}) > M_j(\rho_{2,L}) \geq 0,$$

where $\rho_{2,H} = \rho_2(\theta_H)$, and $\rho_{2,L} = \rho_2(\theta_L)$.

With the two-point distribution of weather, we conclude that harmful weather in the current period reduces the hope of a farmer for her future well being. The farmers who are located at the left tail of the taste-for-living parameter may commit suicide due to the hopelessness caused by the bad weather shock.

Extending this two-year model to an N-year period model, if a farmer experiences successive years of bad weather, her hope for the future becomes bleaker over time, reflected in decreasing values of the M function, in turn raising the likelihood of suicide.

First, define the hope function for the N-period model as the cumulative discounted value of expected utility to describe a farmer's belief of future well-being based on the current and the past profit realization at year n:

$$
\begin{aligned}
M_n(\cdot) &= \sum_{t=n+1}^{N} r^{t-1} EU_t^*(S_{t-1}) \\
&= \sum_{t=n+1}^{N} r^{t-1} \Big(\rho_t(\boldsymbol{\theta_p}) U_H^* \big(x_t^*(\theta_H, S_{t-1}), V(w_t^*(\theta_H, S_{t-1}), l_t^*(\theta_H, S_{t-1})) \big) \\
&+ (1 - \rho_t(\boldsymbol{\theta_p})) U_L^* \big(x_t^*(\theta_L, S_{t-1}), V(w_t^*(\theta_L, S_{t-1}), l_t^*(\theta_L, S_{t-1})) \big) \Big),
\end{aligned}
\tag{11}
$$

where $\boldsymbol{\theta_p}$ is a vector of all the past weather realizations. A farmer's perception for future weather at year n is ρ_{n+1} , where ρ_{n+1} is a function of all the past weather realizations.

$$
\rho_{n+1}(\boldsymbol{\theta_p}) = \rho_{n+1}(\theta_n, \theta_{n-1}, ..., \theta_2, \theta_1).
$$

As time moves on, a farmer updates her perception of future weather probability based on past years' weather observations. We could apply the similar updating function for other exogenous factors. For the simplicity of illustration, we hold other exogenous factors as constant here.

Thus, a farmer at year n maximizes $U_n + \sum_{t=n+1}^{N} r^{t-1} EU_t^*(S_{t-1})$, i.e., her current utility plus the discounted expected utility given her belief of future weather shocks. She anticipates her future optimal choices of farm variable inputs z^*, consumption goods level x^*, work effort w^* recursively, starting from the last period, N, and planning backwards year by year to period $n+1$. Then, based on her future anticipation decisions, she maximizes $U_n + \sum_{t=n+1}^{N} r^{t-1} EU_t^*(S_{t-1})$ choosing z_n, x_n or S_n , and w_n or l_n.[10] Under maximization, a farmer's hope function at year n is a function of future weather shock probability, farm

[10]We can replace x_n with S_n and l_n with w_n since the two constraints in period n bind: $p_x x_n + S_n = Q(w_n, z_n, \theta_n) - p_z z_n + W_n + S_{n-1}$ and $w_n + l_n = T$.

variable input price, consumption price, output price, her discount factor and interest rate. She updates her hope function each period when there is one more observation of past weather shock.

$$M_n(\rho_{n+1}(\boldsymbol{\theta_p}), p_z, p_x, p, \gamma, r, W_{n+1})$$

A farmer j's suicide decision is defined by equation (12). If at year n, a farmer's hope function plus her taste of living parameter become non-positive, she may commit suicide.

$$M_{j,n}(\rho_{n+1}(\boldsymbol{\theta_p}), p_z, p_x, p, \gamma, r, W_{n+1}) + b_j \leq 0 \tag{12}$$

As a farmer experiences bad weather for some successive years, especially when it is believed to be related to climate change, her perception of the probability of having bad weather increases as she updates ρ_{n+1}, and future poor farm income that may be caused by her believed future bad weather. With the perception of getting constantly restrained budgets and the intense work effort that a farmer rationally has to invest to minimize the loss in profits, the hope of a farmer diminishes year by year, until at some period when her hope approaches zero. Weather is one of the potential factors that cause poor farm income, which when endured for successive years may cause suicide.

Similarly, if we hold other variables constant and allow one of the economic variables to vary, we can derive the same "snowballing" effect that when a farmer faces volatile input and/or output prices for successive years, her perception of the probability of having volatile prices rises as she updates her function of perceived future price based on her past price realizations, which leads to her belief of having poor farm income. Thus, chronic poor economic conditions may induce farmer suicide.

In conclusion, based on the theoretical model we have the hypotheses that i) the marginal effect of beneficial weather on farmer suicide is negative, ii) the marginal effect of harmful weather on farmer suicide is positive, and (iii) successive realizations of bad weather and/or bad economic conditions can have a "snowballing" effect on suicide decisions through their impacts on expectations of future weather. In the next section, we test the above hypotheses derived from the theoretical model using empirical methods.

4 Empirical Analysis

This study analyzes the relationship between the annual farmer suicide rate, measured for each U.S. county as a function of economic conditions impacting farm income in both levels and variability and cumulative exposure to beneficial/harmful temperature and rainfall during the crop growing season using a fixed-effect regression model that accounts for time-invariant differences across agricultural regions in unobservable determinants of the suicide rate.

4.1 Data and Variable Construction

There are three major data sources for this study: CDC mortality data, daily weather data, and economic data in the U.S. Our access request to the CDC non-public vital statistics database was approved by CDC's National Association for Public Health Statistics and Information Systems (NAPHSIS) and the National Center for Health Statistics (NCHS). The daily weather data and economic data are publicly available.

Nonpublic Vital Statistics Data

The CDC nonpublic vital statistics data records the individual death occurrence by multiple causes of death from 1999 to 2017 at the U.S. county level. These data help to identify occurrences of farmer suicides, the population of interest for this study, by selecting the "place of injury" variable as "farm" and "manner of death" variable as "suicide", where I use individuals who committed suicide at a farm as a proxy for farmers having committed suicide.

Suicides occurring at a farm is an imperfect proxy for suicides committed by farmers, but evidence suggests it is a good proxy. One of the potential concerns is that many retirees live in rural areas that might be classified as farms by the USDA definition, even though very little farming is conducted on them. According to the USDA definition, any place that produced and sold at least $1000 of agricultural products in a given year is treated as a farm. For example, if someone turns his or her property into a small farm to raise goats or alpacas, or grow grapes and sells a small amount of product, this enterprise is treated as a farm even though the proprietors are not engaged actively in farming.

However, the CDC does not use the USDA definition for farm. The CDC definition involves what it considers to be farm locations. Below are the places that the CDC considers as a farm according to the vital statistics data instruction:

"Barn NOS (not otherwise specified), Barnyard, Corn crib, Cornfield, Dairy (farm) NOS, Farm buildings, Farm pond or creek, Farmland under cultivation, Field, numbered or specialized, Gravel pit on farm, Orange grove, Orchard, Pasture Ranch NOS, Range NOS, Silo, State Farm (excludes: farm house and home premises of farm)."

These locations are farm business places where extensive farming activities are conducted. This alleviates the concern about mistakenly classifying people living in a non-commercial farm place as a farmer.

Most farmers in the U.S. live on farms. Although a farmer who dies by suicide need not take his or her life on the farm, non-farmers who committed suicide are unlikely to take their lives on a farm, so the direction of bias seems clear: farmer suicides are likely to be under counted by my definition.

To provide some statistical evidence on the accuracy of the suicide-on-farm proxy, I examined CDC statistics on the male suicide rate for farmers, ranchers, and other agricultural managers (SOC 11-9013), reported as a subgroup of the Managers major group. The rate was 44.9 (per 100,000) in 2012 from 17 states. The public-use mortality data shows that 167 males committed suicide at farms in 2012. The population of farmers, ranchers, and other agricultural managers in 2012 was 538,314, as reported by U.S. Census Bureau (United States Census Bureau, 2017). Dividing 167 by 538,314 yields a rate of suicides committed at farms in 2012 of 31.02 per 100,000, somewhat below that but of the same order of magnitude as the CDC value. In 2015, the gap is even less. the CDC-reported suicide rate for farmers was 32.2 per 100,000, whereas the rate for suicides committed on farms was 36.97.

The calculation in more years can be found in Table 4, which shows the number of male suicides-on-farm, the number of male farmers, and the male farmer suicide rate from 2005 to 2017.

Table 4: Male farmer suicide counts and rates, Age≥16, 2005-2017, U.S. total

Year	Count Suicide-on-farm	Population (SOC 11-9013)	Rate (per 100,000)
2005	212	579,603	36.58
2006	204	599,115	34.05
2007	201	587,015	34.24
2008	188	532,561	35.30
2009	193	522,659	36.93
2010	217	527,029	41.17
2011	202	513,352	39.35
2012	167	538,314	31.02
2013	200	539,320	37.08
2014	211	504,437	41.83
2015	186	503,142	36.97
2016	103	479,184	21.49
2017	218	458,234	47.57

Source: CDC, 2019.

Note that the CDC-reported suicide rates and the suicide rates at farms are not directly comparable since the CDC reports the suicide rate for 17 states, which largely excludes the major agricultural states, whereas our calculations are based on all states. Nonetheless, we are encouraged by the comparative closeness of the suicide rates.

The nonpublic mortality data allow us to do a more precise comparison to further support the validity of the proxy selecting the same states included in the CDC report. Table 5 represents the on-farm counts and rates in 2012 and 2015 using the CDC nonpublic data from the same states reported in the CDC article, except for Alaska.[11] The closeness of both suicide count and rate affirm our conclusion that suicide committed on a farm is a good proxy for farmer suicide.

Table 5: Farmer and on-farm suicide count and rate comparison

Sample Year	On-farm count (16 states)	CDC count (17 states)	On-farm rate (16 states)	CDC rate (17 states)
2012	48	59	34.7	44.9
2015	59	54	45.3	32.2

Source: CDC, 2019.

For each record of suicide occurrence, information about the decedent's age, sex, race, resident status, education (years of schooling and/or degree level), month of death, day of week of death, place of death (hospital/clinic/home/hospice facility/nursing home/other), marital status, injury at work (yes/no/unknown) are also provided. This individual-level data set allows us to develop a preliminary analysis of the demographic characteristics of farmer suicides. The summary statistics of the individual-level data are displayed in the next subsection. Given each farmer suicide occurrence happened in a county in a year, I convert the individual-level vital statistics data to panel data with the farmer suicide count at the county level from 1999 to 2017.

[11] Alaska is excluded in the nonpublic vital statistics data, but is included in the CDC report.

Weather Data

For daily temperature data, I use the raw daily temperature data from Wolfram Schlenker's website.[12] The raw data files give the daily minimum and maximum temperature, as well as total precipitation on a 2.5×2.5 mile grid for the contiguous United States from 1900 to 2017, which is based on the PRISM weather data set. Each grid-cell datum is a weighted average of the ten surrounding weather stations. I convert daily temperature into annual observations according to the agronomic concept of degree day.

The concept of growing degree day is a special case of time-separable growth, typically defined as the sum of truncated degrees between two bounds. For example, Ritchie and Nesmith (1991) have suggested bounds of 8°C and 32°C for beneficial heat. A day of 9°C hence contributes 1 degree day, a day of 10°C contributes 2 degree days, up to a temperature of 32°C, which contributes 24 degree days. All temperatures above 32°C also contribute 24 degree days.

Denoting the bound as b, I follow Schlenker's sine interpolation of daily temperatures for reference to compute degree days (DD) bounded by temperature b as follows:

$$DD_b(t_{min}, t_{max}) = \begin{cases} 0 & \text{if } t_{max} \leq b, \\ t_{avg} - b & \text{if } b \leq t_{min}, \\ \frac{\left((t_{avg}-b)\times\tau+\frac{1}{2}(t_{max}-t_{min})\times\sin\tau\right)}{\pi} & \text{if } t_{min} < b < t_{max}. \end{cases} \tag{13}$$

[12]The daily weather dataset is available at http://www.wolfram-schlenker.com/dailyData.html. These data are based on Oregon State University PRISM Gridded Climate Data, commonly used and cited in environmental economic research. See for example Burke et al. (2018) and publications of Wolfram Schlenker, such as Schlenker and Roberts (2009).

where t_{min} and t_{max} are the daily minimum and maximum temperature values. t_{avg} is defined by the average value of the daily maximum and minimum temperature. In the third case,

$$\tau = \arccos \frac{2b - t_{max} - tmin}{t_{max} - tmin}.$$

Thus, the daily degree days is calculated as follows: $DD(\boldsymbol{t}_d) = DD_{b,d}$, denoting $\boldsymbol{t}_d$ as the daily temperature information, i.e., $t_{min,d}$ and $t_{max,d}$ in day d. For example, degree days above 10°C in a single day d can be denoted as $DD_{10,d} = DD_{10}(t_{min,d}, t_{max,d})$.

There has been some controversy whether and at what point temperatures become harmful, especially when sufficient water can be applied to a crop. Researchers have applied various degree cutting points to the upper bound of beneficial temperature range. For example, Schlenker and Roberts (2009) find that yields increase with temperature up to 29°C for corn, 30°C for soybeans, and 32°C for cotton but that temperatures above these thresholds are very harmful. Roberts and Schlenker (2011) have implemented degree days between 10°C to 29°C as the beneficial range, and degree days above 29°C as the harmful range. Lobell et al. (2017) define extreme degree days as the cumulative degree days above 30°C. Schlenker et al. (2006) use bounds of 8°C and 32°C for growing degree days, and above 34°C for harmful degree days. To avoid such controversy, some researchers exclude the concept of harmful degree days in their analysis (Schlenker et al., 2007), or use a single bound to model the cumulative heat during the growing season, which reflects both the beneficial and harmful part of heat.

I use 10°C as the value of b throughout the study. I have examined robustness for other plausible bounds such as 8°C, bounds of 8°C and 32°C for growing degree days and above 32°C for harmful degree days. The robustness of alternative bounds such as 10°C and 34°C is also examined. The alternative regression results are included in the Appendix.

The grid-level daily degree days are then summed over the entire growing season, which is usually defined based on the crop-growing months, such as during March to August (Schlenker & Roberts, 2009) or from April to September (Schlenker et al., 2007). In this study, the growing season is defined as from March through September. $\sum_{d=1}^{D} DD(\boldsymbol{t}_d)$ denotes the cumulative growing degree day from day one to day D, where $d = 1$ stands for March 1$^{\text{st}}$. $d = D$ represents September 30$^{\text{th}}$, the last day in the growing season in a year. Next, the cumulative daily degree days at each grid cell during the growing season are aggregated to the county level using cropland area weights.[13]

Similarly, the precipitation levels are initially available for each day at each grid cell during the growing season (March to September). Then, they are aggregated for the whole growing season from the first day of March through the last day of September. Finally, they are aggregated to the county level using cropland area weights.

The two weather variables in this study, county-year level cumulative degree days above 10°C and precipitation, are joined with the variable of interest, farmer suicide count at county-year level, as panel data.

Economic Index

We want to construct an economic index as a variable in our model to explain farmer suicides. Suppose in county i, there are n leading agricultural products $c = 1, 2, ..., n$. The national price of product c in year t is p_t^c, where $t = 1999, ..., 2017$. I convert the nominal price to real

[13] The cropland area data at grid level are also available at Wolfram Schlenker's website.

price P_t^c (in 2017 \$) using the CPI (United States Bureau of Labor Statistics, 2019). The average real price of product c over the 19-year period is $\bar{P}^c$:

$$\bar{P}^c = \sum_{t=1999}^{2017} \frac{P_t^c}{19}.$$

In each year t, there is a deviation of the real price from the average real price for each product, $D_t^c = \log(P_t^c) - \log(\bar{P}^c)$. The average total sales of product c in county i in real terms is s_i^c. There are n total leading products in a county. Thus, each product has a weight defined by the percentage of the average sales of product c of the total sales of the n leading products in this county.

$$r_i^c = \frac{s_i^c}{\sum_{c=1}^{n} s_i^c}. \tag{14}$$

For each county, the weights sum up to one: $\forall i, \sum_{c=1}^{n} r_i^c = 1$. For a county i in year t, a weighted index can be computed to measure the health of the local agricultural economy, I_{it}:

$$I_{it} = \sum_{c=1}^{n} r_i^c D_t^c. \tag{15}$$

I selected 10 agricultural products according to the USDA cash value ranking (USDA ERS, 2021). They are, in descending order, corn, soybean, wheat, hay, grapes, cattle & calves, milk, broilers, hogs, and chicken eggs. The historical national prices of the ten products from 1999 to 2017 were retrieved from the USDA National Agricultural Statistics Service (NASS). Sales data are available at the county level only in census years.

Some crops are inputs (feed) into livestock production, meaning price changes have an ambiguous effect on economic welfare of farmers—e.g., higher corn prices are good news for corn farmers but bad news for livestock farmers. To avoid this ambiguity, the selected products are categorized into two groups and a crop index and animal index are created separately. Corn, soybeans, wheat, and hay can be feed materials, which I combine to comprise an animal feed index.

Notation	Index name	Component (products)
I_{it}^{C}	Crop index	corn, soybeans, wheat, hay, grapes
I_{it}^{A}	Animal index	cattle & calves, milk, broilers, hogs, chicken eggs
I_{it}^{F}	Animal feed index	corn, soybeans, wheat, hay

An indicator variable is used to identify if a county mainly produces crop or animal products. Each county i has a ratio of the total crop sales to total animal sales:

$$Ratio_i = \frac{TS_i^{Crop}}{TS_i^{Animal}}.$$

Different cutoff points, listed in table 6 below, divide the sample into crop-dominating counties and animal-dominating counties. I use thresholds of 0.75 and 1.25 throughout the study. A county is defined as crop-dominating county, i.e., $D_i^C = 1$, if $Ratio_i > 1.25$. A county is defined as animal-dominating county, i.e., $D_i^A = 1$, if $Ratio_i < 0.75$, and is not dominated if $0.75 \leq Ratio_i \leq 1.25$.

Table 6: Crop- v.s. animal-dominating county selection

Total sales ratio	County number			Total:3009
Cutoff point	Animal	Neither	Crop	Cutoff point
0.75	1392	458	1159	1.25
0.8	1454	365	1190	1.2
0.9	1554	200	1255	1.1

We create two-year and three-year moving average indexes in addition to our designed own-year index to test if prolonged poor economic conditions have a positive effect on farmer suicides. The detailed definition of moving average indexes is listed in table 7.

Table 7: Economic indexes definition

Index name	Own year	Two-year moving average	Three-year moving average
Year range	1999-2017	2000-2017	2001-2017
Crop index	I_{it}^{C}	$\frac{1}{2}(I_{it}^{C} + I_{i,t-1}^{C})$	$\frac{1}{3}(I_{it}^{C} + I_{i,t-1}^{C} + I_{i,t-2}^{C})$
Animal index	I_{it}^{A}	$\frac{1}{2}(I_{it}^{A} + I_{i,t-1}^{A})$	$\frac{1}{3}(I_{it}^{A} + I_{i,t-1}^{A} + I_{i,t-2}^{A})$
Animal feed index	I_{it}^{F}	$\frac{1}{2}(I_{it}^{F} + I_{i,t-1}^{F})$	$\frac{1}{3}(I_{it}^{F} + I_{i,t-1}^{F} + I_{i,t-2}^{F})$

In addition to weather and economic index variables, we incorporate farm population in the model as a control variable. We retrieved the number of farmers at the county level in census years from the USDA NASS. Since the data is only available in census years, farm population in a census year represents the value in the nearest 5 years, i.e., $x_{it} = x_{it^c}$, if $t \in [t^c - 2, t^c + 2]$, suppose x_{it} denotes farm population in county i in year t, and t^c symbolizes one of the census years. For example, the farm population in a county in census year 2012 represents the farm population from 2010-2014 in this county.

I compiled the U.S. suicide, weather, and economic data at the county level for years from 1999 to 2017. Farmer suicide count, growing season cumulative precipitation and degree days, and economic index variables in county-year levels were constructed. The merger of the three data sets and construction of the key variables allow me to identify and relate farmer suicide to weather conditions and health of the agricultural economy for each county during the study period. Thus, hypotheses regarding impacts of weather and economic conditions on farmer suicides can be tested.

4.2 Summary Statistics Analysis

The original CDC nonpublic vital statistics data provides detailed information of each death occurrence. I summarized the individual-level death data by various aspects, including age, sex, race, education level, month of suicide, and manner of suicide of the farmer occurrences, as part of the pre-regression analysis. Although analysis of the summary statistics cannot discern causal relationships between farmer suicides and their demographic characteristics, this analysis helps us better understand which demographic groups are at higher risk for suicide.

Tables in this section show some demographic characteristics of farmer suicides in the U.S. mainland during 1999-2017.[14] There are a total of 4,146 cases of farmer suicide in our selected 19 data years.

Solely looking at farmer suicide demographic data is not quite informative without comparing it with farmers' demographics in general or even with the demographics of the labor force as a whole in the U.S. I list the corresponding demographic characteristics of U.S. farmers and the U.S. labor force based on the data summary statistics provided by USDA NASS and the U.S. Bureau of Labor Statistics.

Sex and race

Table 8 shows the majority of farmers who committed suicide are white males. Based on the USDA NASS data in 2017, there were 3,399,834 U.S. farmers in total, and 64 percent of them are males. However, about 90 percent of the farmers who died by suicide are males. The farmers who committed suicide have a similar race distribution as farmers in general.

[14] The selected data sample excludes the following states and U.S. territories: Alaska, Hawaii, American Samoa, Guam, Northern Mariana Islands, Puerto Rico, and the Virgin Islands.

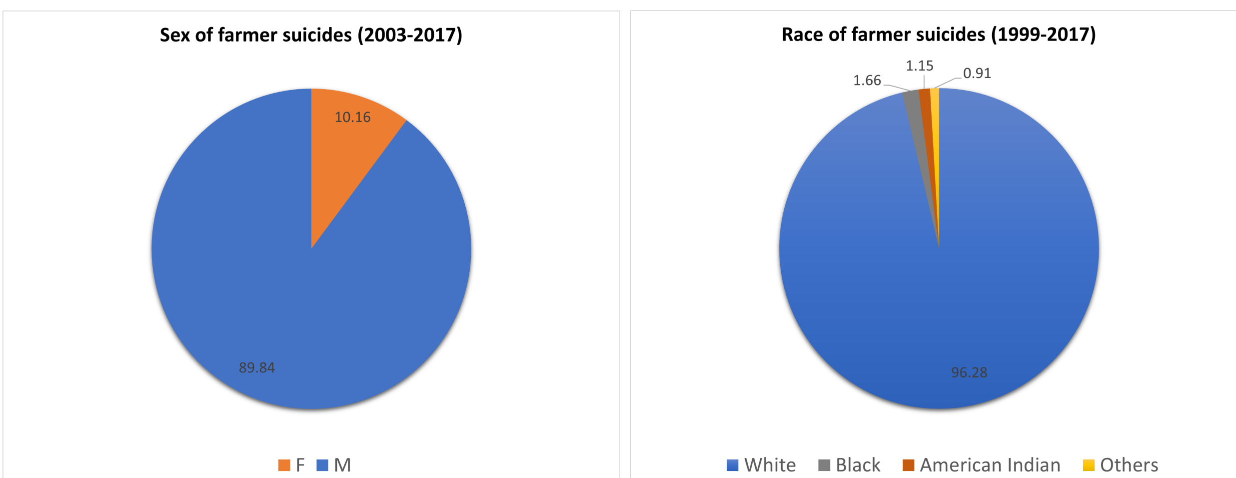
Table 8: Farmer suicide occurrence by sex and race

	Farmer suicide		US farmers(2017 NASS)
Sex (2003-2017)	Number	Percent	Percent
F	334	10.16	36
M	2,952	89.84	64
Total	3,286	100	100
Race (1999-2017)	Number	Percent	Percent
White	4,009	96.28	95.4
Black	69	1.66	1.3
American Indian	48	1.15	1.7
Others	38	0.91	1.6
Total	4,164	100	100

Source: CDC, 2019.

Over 96 percent of farmers are white. Male farmers are at higher risk of suicide, especially white male farmers.

Figure 12: Demographic characteristics of farmer suicide: sex and race



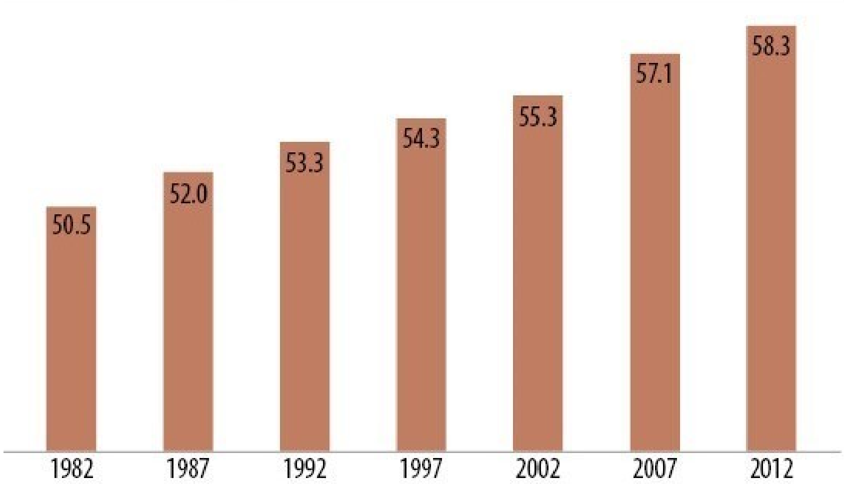
Source: CDC, 2019.

Age

The median age of the labor force in the U.S. has been 42 years since 2000. Farmers, in general, are older than the average the U.S. worker. Figure 13 shows the historical average

age of farmers since 1982 in census years. The average age of an American farmer was 58.3 years old in 2012 and has continued to increase.

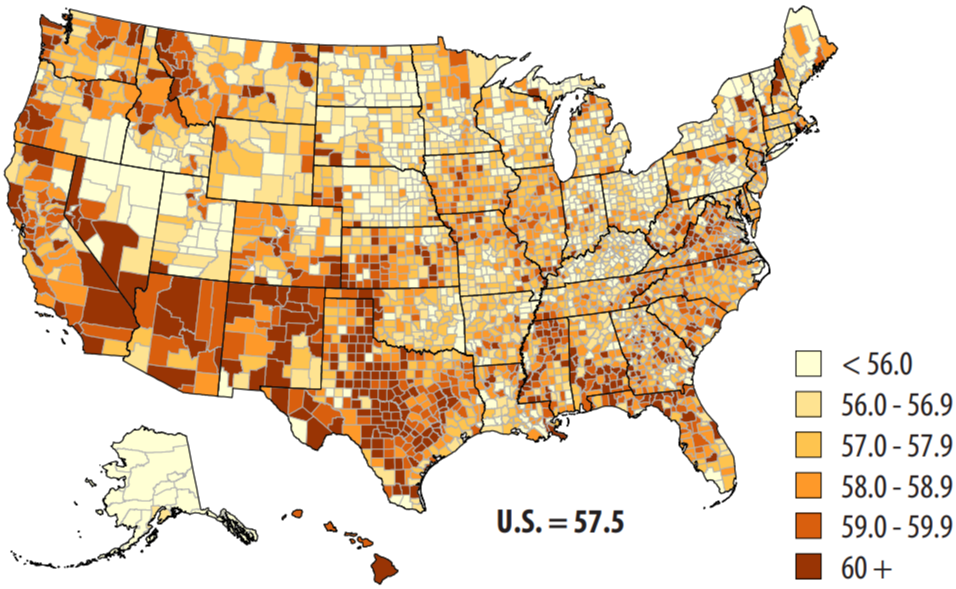
Figure 13: Historical average farmer age in U.S. census years, 1982-2012



Source: USDA NASS, 2012 Census of Agriculture.

Figure 14 shows a map of farmers' average age distribution by county across the U.S. based on USDA NASS data in 2017. On average, farmers are over 56 years old in most places. The average farmer age is even older in the leading agricultural states, such as California and Texas.

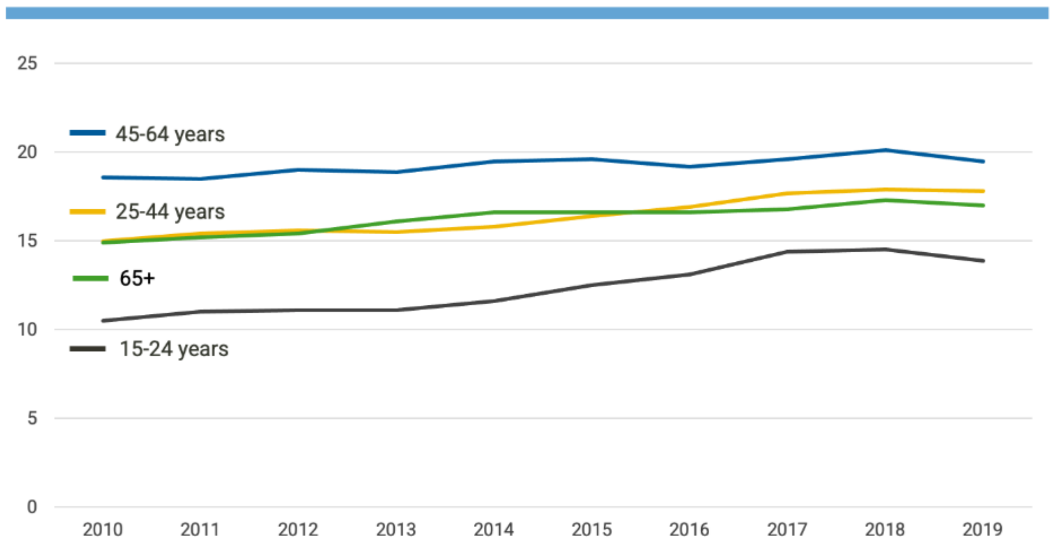
Figure 14: Average farmer age distribution by county in 2017



Source: USDA NASS, 2017 Census of Agriculture.

According to CDC statistics illustrated in figure 15 the suicide rate of the general population is the highest among the age group of 45 to 64 years, which includes a big portion of farmers. The population-aging problem in the farm sector suggests that farmers are at higher risk of suicide compared to people in other occupational groups.

Figure 15: Suicide rates of the general population by age in the U.S., 2010-2019



Source: CDC, 2021.

Note: Y-axis measures number of suicides per 100,000 people.

Table 9 summarizes the number of farmer suicide decedents by age group. More than half of the farmers who committed suicide are over 45 years old. 38.16 percent of farmers who died by suicide in this sample fall into the high suicide risk age group, 45 to 64 years old.

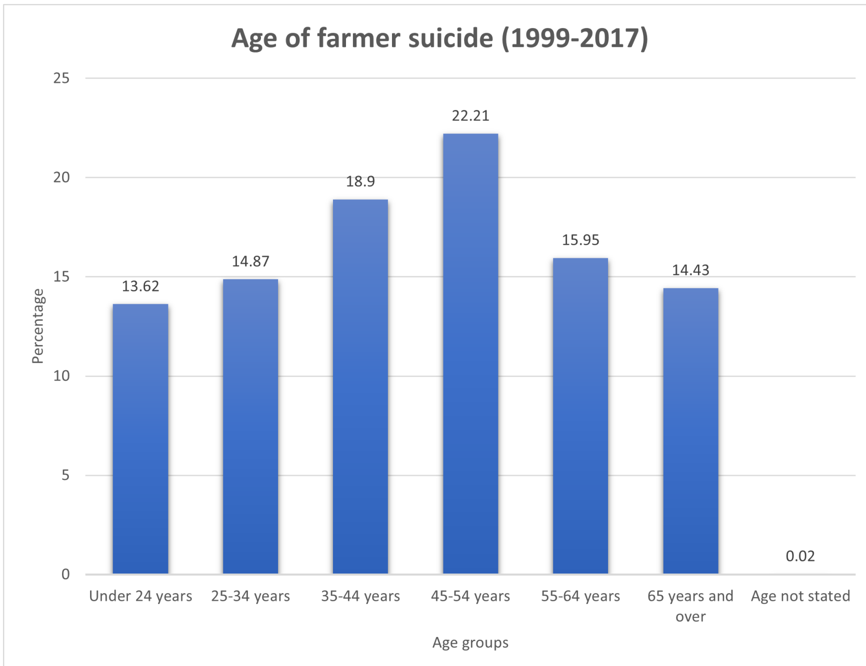
Table 9: Farmer suicide occurrence by age group

Age	Number	Percent
Under 24 years	567	13.62
25-34 years	619	14.87
35-44 years	787	18.90
45-54 years	925	22.21
55-64 years	664	15.95
65 years and over	601	14.43
Age not stated	1	0.02
Total	4164	100

Source: CDC, 2019.

Based on the age distribution in figure 16, the mean age of farmers who committed suicide, between 40 to 50 years old, is younger than the mean farmer age, 58 years old. This indicates that middle-aged farmers are at a higher risk of suicide and suggests that many farmer suicides are not associated with age-related issues.

Figure 16: Percentage share of farmers died by suicide by age range, 1999-2017



Education

The majority of the farmers' with death by suicide have an education level of high school or lower. Only 27.16 percent of the farmers who committed suicide attended college. The detailed number and percentage of farmer suicide occurrence by education level is listed in table 10.

Due to lack of data on educational information for farmers, the educational attainment percentage in rural areas in 2000 and 2018 is used as a proxy to the education level of farmers, with results shown in figure 17. The rural population attained higher levels of education from 2000 to 2018. In 2000, only 40.2 percent of the rural population had attended college. In

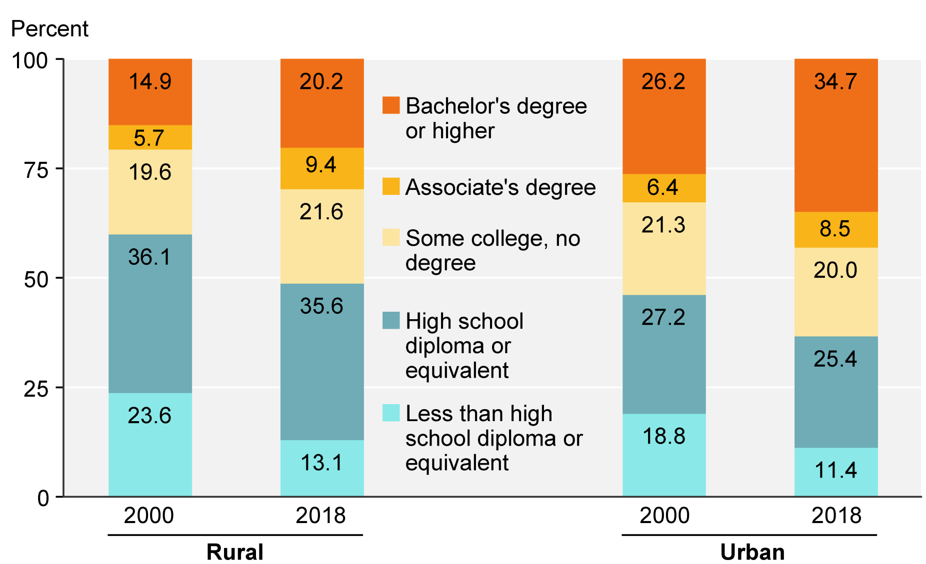
Table 10: Farmer suicide occurrence by education level

Education	Number	Percent
Elementary school or less	367	8.81
High school* or GED	2368	56.87
College*	1131	27.16
Master's or Doctorate or professional degree	170	4.08
Not stated/Unknown	128	3.07
Total	4164	100

*with and without diploma
Source: CDC, 2019.

2018, more than half of the rural population had attended college. The percentage of the population who attended less than high school or equivalent institutions has dramatically decreased from 2000 to 2018. However, only 31.24 percent of farmers who died by suicide have attended college. About two-thirds of farmers who died by suicide just attended high school or elementary school, suggesting that farmers with lower education are at higher risk of suicide.

Figure 17: Educational attainment in rural and urban areas, 2000 and 2018



Note: Educational attainment for adults 25 and older. Urban and rural status is determined by Office of Management and Budget's 2015 metropolitan area definitions.
Source: USDA, Economic Research Service using data from U.S. Department of Commerce, Bureau of the Census, Census 2000 and 2018 American Community Survey.

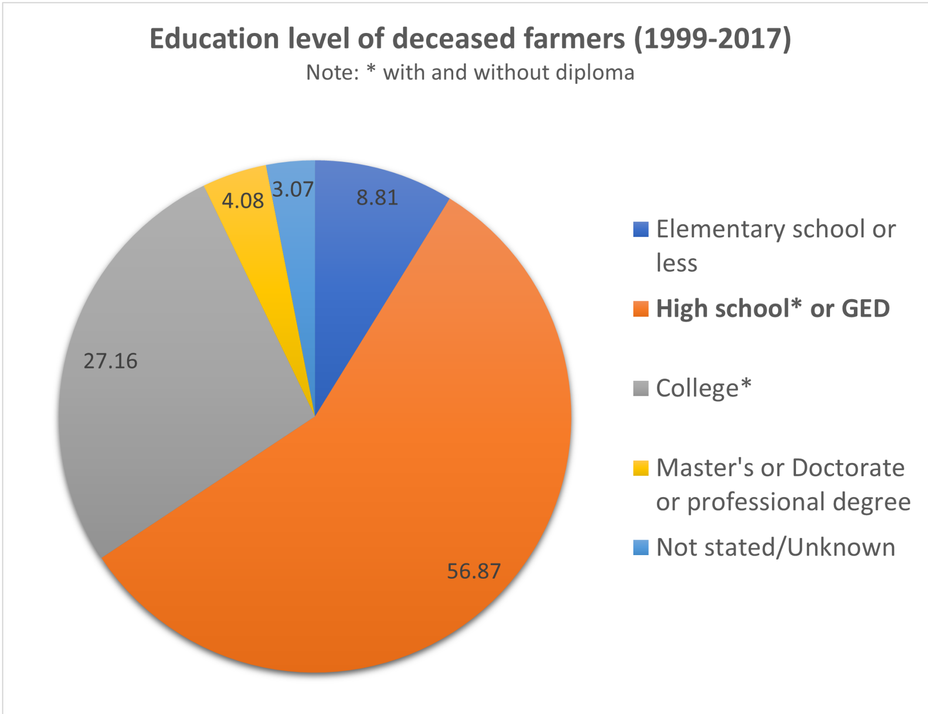


Figure 18: Education level of deceased farmers

Month of suicide

There is no specific pattern of the month of suicide for farmers, despite the fact that summer has a slightly higher percentage. Winter has the lowest percentage of suicide occurrences.

Table 11: Farmer suicide occurrence by the month of suicide

Season	Count	Percent
Spring	1098	26.37
Summer	1164	27.95
Fall	1024	24.59
Winter	878	21.09
Total	4164	100

Source: CDC, 2019.

Manner of suicide

More than half of the farmers committed suicide by using firearms. This is consistent with the existing research, such as (Stallones et al., 2013), about access to lethal means leading to a higher suicide rate for farmers. The second most common manner of suicide for farmers was hanging, strangulation, and suffocation. Other manners are listed in table 12.

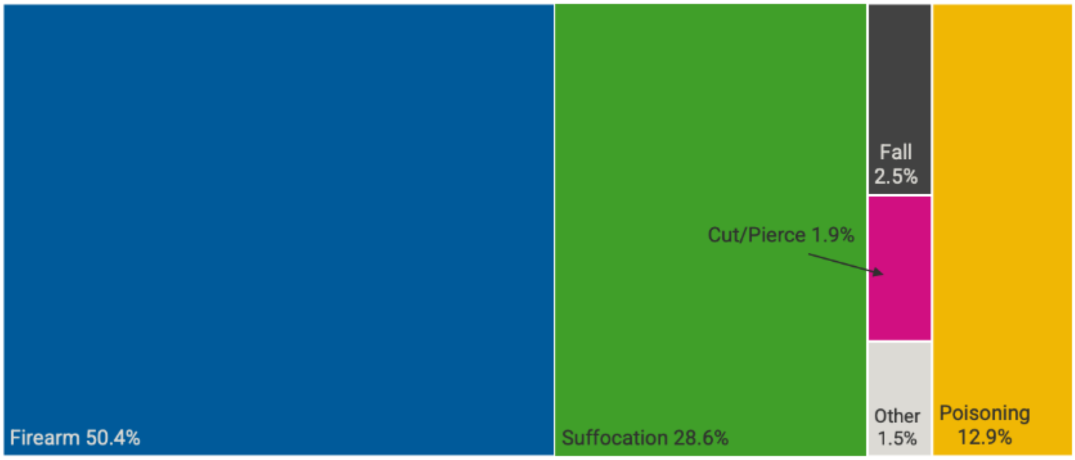
Table 12: Farmer suicide occurrence by the manner of suicide

Manner of death (1999-2017)	Count	Percent
Intentional self-poisoning	281	6.75
Hanging, strangulation and suffocation	1,304	31.32
Discharge of firearms	2,424	58.21
Jumping from a high place	23	0.55
All other and unspecified means and their sequelae	132	3.17
Total	4164	100

Note: Sequelae refers to conditions which are the consequence of a previous disease or injury.
Source: CDC, 2019.

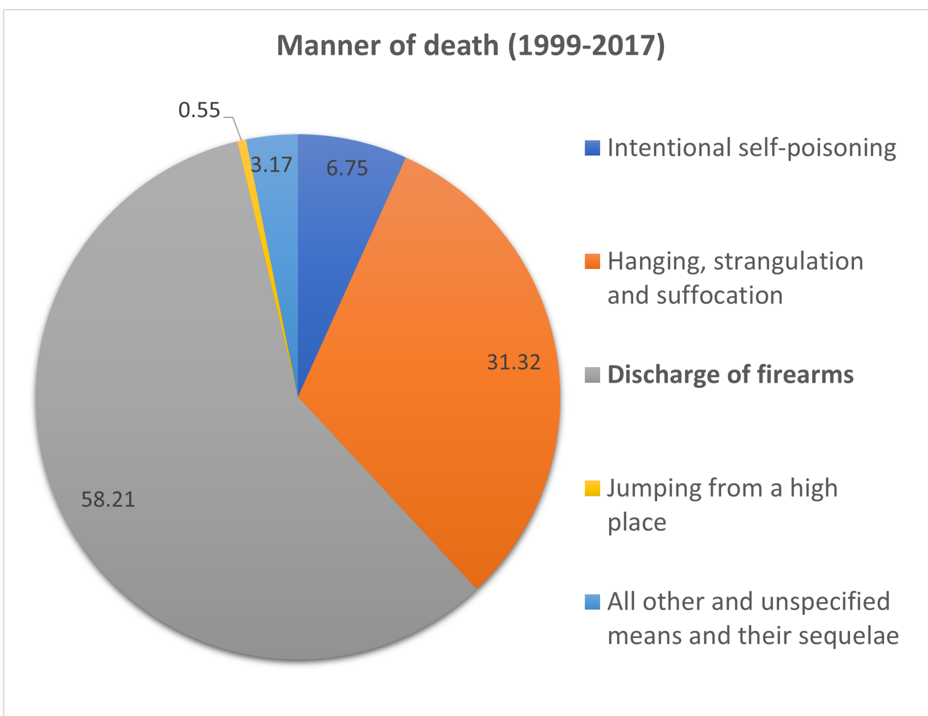
Discharging firearms is also the most common means of suicide among the general population. Comparing figure 19 and figure 20, farmers are more likely to choose firearm as their means of suicide. This potentially is because it is conventional to own and use firearms in farming practices, especially for livestock farmers. For example, a gun can be a handy tool for protecting livestock and poultry from predators and keeping their farmland intact from wild animals. Firearms are one of the utilitarian tools for farmers and people living in a rural environment. It is also easier for farmers to legally apply for firearm ownership certificates compared to people in other occupational groups, in general.

Figure 19: Manner of suicide among the general population in the U.S., 2019



Source: CDC, 2021.

Figure 20: Manner of farmer suicide



Source: CDC, 2019.

I utilize the nonpublic mortality data and merge it with the weather data and economic data to conduct empirical analysis of the causal relationship between farmer suicide and weather and economic conditions. The data are in county-year strongly balanced panel structure with 3037 counties from 48 states spanning from 1999 to 2017.

Table 13 provides summary statistics for key variables of interest in the analysis. Note that the variable *farmer suicide count* measures the farmer suicide count in a county in a year.

Table 13: Summary statistics for key variables, full sample

Variable	Mean	Std. Dev	Min	Max
Farmer suicide count	0.07	0.28	0.00	5.00
Precipitation (mm)	637.93	254.26	6.05	2153.64
Average temperature	18.29	3.82	6.09	29.07
Degree days above 8°C (DD8)	2388.41	674.67	603.15	4516.20
Degree days above 10°C (DD10)	2032.20	632.80	435.50	4095.30
Growing degree days 8°C-32°C	2367.69	654.00	603.15	4179.97
Growing degree days 10°C-34°C	2024.733	624.1241	435.496	3883.569
Degree days above 32°C (HDD32)	20.72	35.20	0.00	535.97
Degree days above 34°C (HDD34)	7.47	19.37	0.00	384.42
Number of Observations: 57,703				

Suicide count as the dependent variable and the weather variables as regressors both can vary over time and across counties. Table 14 shows within and between variation of the key variables, where "within" denotes the variation over time for a given county and "between" denotes the variation across counties. Time-invariant variables have zero within variation. In the fixed effect model, the coefficient of a regressor with little within variation will likely be imprecisely estimated and will not be identified if there is no within variation at all.

The variations of farmer suicide count come more from within than between variations. Degree days above 10°C, degree days above 34°C and cumulative precipitation have higher

Table 14: Within and between variations for key variables

Variable		Mean	Std. Dev.	Min	Max
Farmer suicide count	overall	0.07	0.28	0.00	5.00
	between		0.10	0.00	1.74
	within		0.26	-1.67	3.44
Growing season cumulative weather variables					
Precipitation(mm)	overall	637.93	254.26	6.05	2153.64
	between		212.58	27.23	1251.06
	within		139.54	71.97	1800.72
Degree days above 8°C	overall	2388.41	674.67	603.15	4516.20
	between		663.51	703.95	4346.55
	within		122.76	2039.09	2910.05
Degree days above 10°C	overall	2032.20	632.80	435.50	4095.30
	between		622.04	525.16	3927.90
	within		116.73	1704.76	2550.42
Degree days above 32°C	overall	20.72	35.20	0.00	535.97
	between		31.38	0.00	469.58
	within		15.96	-90.93	208.30
Degree days above 34°C	overall	7.47	19.37	0.00	384.42
	between		17.16	0.00	328.97
	within		9.01	-63.69	143.75
Average daily temperatures					
Min temperature(°C)	overall	11.68	4.09	-2.69	22.57
	between		4.04	-1.18	21.72
	within		0.64	9.27	13.96
Max temperature(°C)	overall	24.91	3.78	14.02	37.45
	between		3.67	15.46	36.68
	within		0.92	21.71	29.21
Average temperature(°C)	overall	18.29	3.82	6.09	29.07
	between		3.75	7.22	28.27
	within		0.72	15.70	21.37
Economic index variables					
Crop index	overall	-0.03	0.23	-0.48	0.61
	between		0.01	-0.05	-0.01
	within		0.23	-0.48	0.63
Animal index	overall	-0.02	0.17	-0.36	0.54
	between		0.01	-0.02	-0.01
	within		0.17	-0.35	0.54
Number of observations: overall N=57,703, between n=3037, within T=19.					

between variation than within variation, as expected. Thus, within estimation may lead to considerable efficiency loss. This table suggests that the fixed effect model is suitable to predict the association between farmer suicide and weather variables. The Min and Max columns give the minimum and maximums of x_{it} for overall, $\bar{x}_i$ for between, and $x_{it} - \bar{x}_i + \bar{x}$ for within,[15] where i and t denote county and year, respectively.

Suicide counts in a county in a year vary between 0 and 5 in the data. Average farmer suicide count for each county varied between 0 and 1.737. Farmer suicide count within county varied between -1.665 and 3.440, where the within number refers to the deviation from each county's average. For example, a county has 0 farmer suicide in year 1999 and one farmer suicide in the rest of 18 years from 2000 to 2017. The "within" number in 1999 of this county is calculated as: $x_{it} - \bar{x}_i + \bar{x} = 0 - \frac{18}{19} + 0.07 = -0.88$.

Weather by Suicide Count

Analyzing the tabulation of weather variables by farmer suicide count provides some intuitive understanding of the relationship between weather and farmer suicide. Table 15 provides summary statistics for the three weather variables by three categories of farmer suicide count in a county in a year: zero suicide, one suicide, and two or more suicides. Higher farmer suicide counts are associated with lower precipitation levels. Harmful degree days (degree days above 32°C), denoted as HDD32, are associated with increasing farmer suicides. Growing degree days between 8°C and 32°C, denoted as GDD32, are associated with slightly lower farmer suicide counts.

Figure 21 displays the summary statistics of weather variables by farmer suicide count

[15] The global mean $\bar{x}$ is added back in make results comparable.

Table 15: Means of the weather variables by farmer suicide count

Count[a]	Observation	Precipitation(mm)	GDD(8-32)	HDD32
0	53,895	638.67	2368.52	20.66
1	3,521	632.59	2355.83	20.89
2,3,4,5	287	563.88	2357.55	30.84

[a] Farmer suicide count in a county in a year.

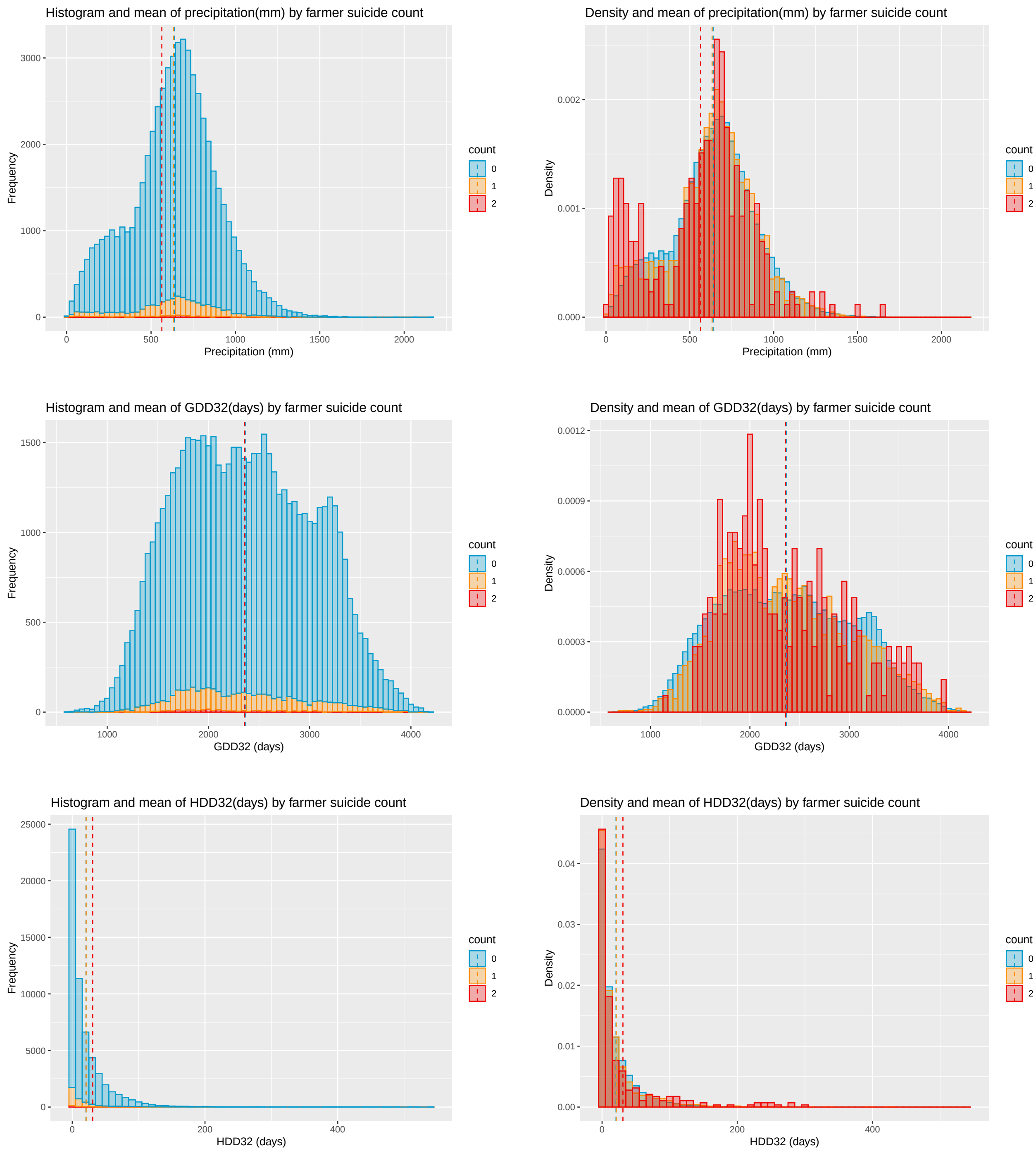
more explicitly. The dashed lines represent the mean value of the weather variables in each category, where category 2 (in red color) denotes the category with two and more farmer suicide counts. All of these qualitative results are consistent with our hypotheses. Note that these statistics only suggest the association relationship between weather and farmer suicide. We need regression analysis to show if there exists any causal relationship between farmer suicide and the weather variables.

As figure 21 illustrates, the distributions of HDD is highly right skewed, reflecting that the U.S. has a handful of very hot counties. Agriculture in these counties consists mainly of crops, such as vegetables, grown during the winter months. For example, the main agricultural commodities in Imperial county in Southern California are winter vegetables, such as broccoli, cauliflower, and carrots.

Given that the growing season for these counties is counter to the growing season specified in the main model and their main agricultural products are not part of our crop and animal indexes, we dropped the observations of the top 1% highest HDD34 counties (32 counties) located in Arizona (6 counties), California (2 counties), Nevada (1 county), Oklahoma (1 county), and Texas (22 counties).[16]

[16] Dropped counties include: Gila, Lapaz, Maricopa, Mohave, Pinal, and Yuma in Arizona; Imperial and San Bernardino in California, Clark in Nevada; Jackson in Oklahoma; Archer, Baylor, Brooks, Dimmit, Duval, Foard, Frio, Hardeman, Haskell, Jim Hogg, Jones, Knox, La Salle, Marverick, McMullen, Presidio, Starr, Wichita, Wilbarger, Young, Zapata, and Zavala in Texas.

Figure 21: Histogram and density of weather variables by farmer suicide count with mean values in each category in dashed lines



Note: Count 0, 1, and 2 in legend denote categories of zero, one, and 2 and more farmer suicide count groups, respectively.
Mean values of precipitation and degree days above 32°C (HDD32) given farmer suicide count is 0 and 1 are very close. The three dashed lines represent mean values of growing degree days 8°C to 32°C (GDD32) given farmer suicide count is 0, 1, and 2 are very close.

Table 16 shows the summary statistics of the key variables after dropping the handful of observations associated mainly with winter agriculture. All the following regression analysis is based on this sample. Table 17 presents the percentile distribution of the degree days variables.

Table 16: Summary statistics for key variables

Variable	Mean	Std. Dev	Min	Max
Farmer suicide count	0.07	0.28	0	5
Precipitation (mm)	641.00	252.81	9.94	2153.64
Average temperature	18.22	3.76	6.09	28.31
Degree days above 8°C	2373.91	661.90	603.15	4349.81
Degree days above 10°C	2018.29	620.06	435.50	3925.89
Growing degree days 8°C-32°C	2355.01	644.76	603.15	4124.45
Growing degree days 10°C-34°C	2011.91	613.73	435.50	3792.73
Harmful degree days 32°C	18.90	28.01	0	302.70
Harmful degree days 34°C	6.39	13.54	0	200.85
Number of observations: 57,095				

Table 17: Percentile distribution of weather variables

Percentile	DD8	DD10	GDD8-32	GDD10-34	HDD32	HDD34
Min	603.15	435.50	603.15	435.50	0.00	0.00
1%	1125.60	867.43	1125.36	867.38	0.00	0.00
5%	1369.85	1086.62	1368.35	1086.37	0.00	0.00
10%	1521.84	1225.57	1519.56	1225.11	0.07	0.00
25%	1842.14	1518.95	1837.81	1517.59	1.16	0.02
50%	2338.13	1976.87	2327.59	1973.90	7.62	0.99
75%	2884.06	2492.53	2856.10	2483.19	25.51	6.49
90%	3293.69	2885.43	3247.15	2868.39	52.53	18.92
95%	3460.53	3044.96	3406.73	3027.34	75.09	30.99
99%	3770.56	3347.24	3703.70	3318.26	125.60	62.19
Max	4349.81	3925.89	4124.45	3792.73	302.70	200.85

4.3 Regression Methods

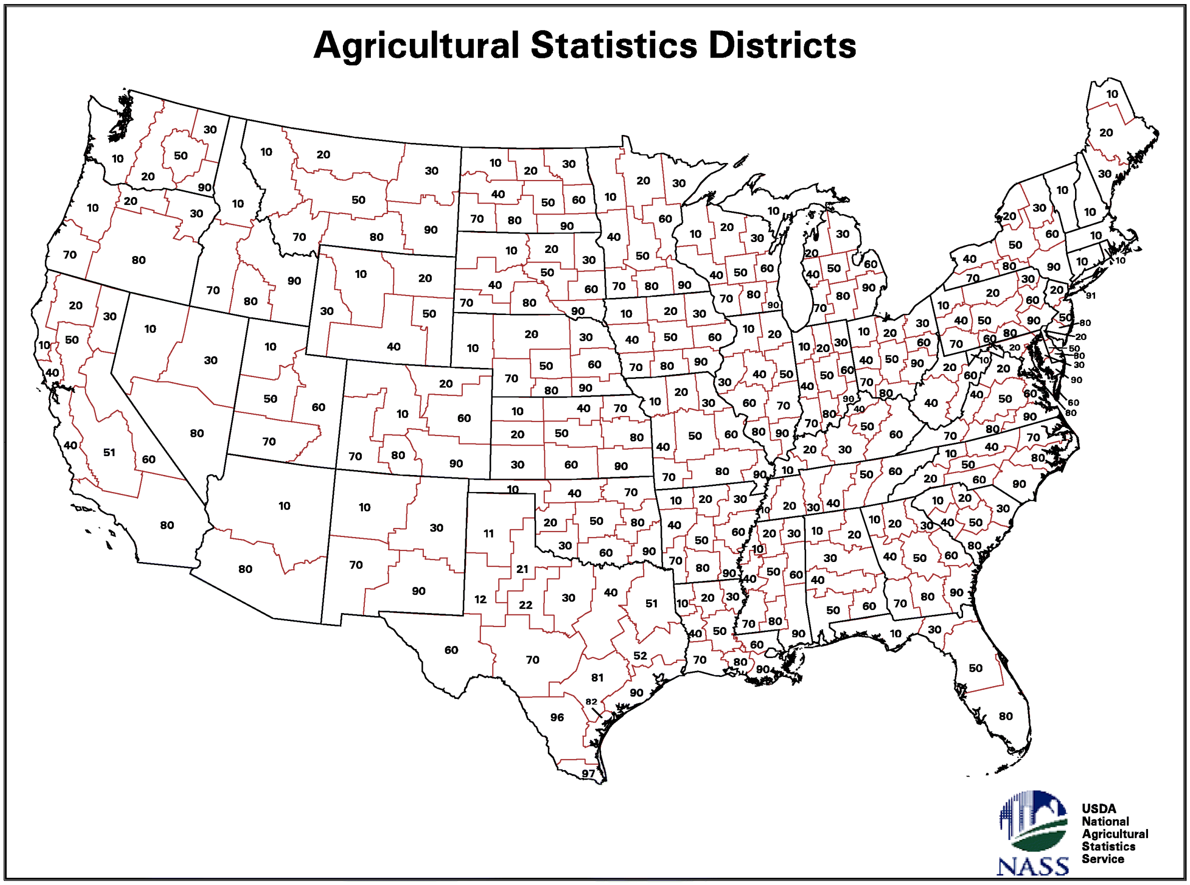
Given that the outcome of interest, namely the farmer suicide count, is a non-negative integer, we estimate a multivariate non-linear panel regression using a Poisson model as a starting point to identify the impact of temperature and precipitation on annual farmer suicide numbers, treating within-county variation in degree days, cumulative precipitation, and economic indexes as exogenous variables.

Cross-sectional variation is potentially endogenous. For example, some time-invariant regional-specific features comprised of economic, cultural, and political factors are possibly correlated with both farmer suicide and weather and economic variables. Leaving such features in the residuals causes omitted variable bias. Therefore, we use fixed effects to control for time-invariant unobservables.

In the county fixed effect Poisson models, a county will be dropped out of the regression if the farmer suicide count is zero during all the 19 data years. In our dataset, there are 1219 such counties with zero farmer suicide counts for the entire data set. Using county fixed effects loses much information in those counties. Therefore, we use Agricultural Statistics District fixed effects in the following analysis to maximize the utilization of the data and preserve its representativeness of farmer suicides in the U.S.

Agricultural Statistics Districts (ASD), presented in figure 22, are defined groupings of counties in each state, by geography, climate, and cropping practices. For example, the geographic attributes include soil type, terrain, and elevation (mountains). The magnitude of an agricultural district is larger than a county and smaller than a state. ASD is an ideal fixed effects level to control for unobservable cross-sectional variations because it reflects an area with similar agricultural activities, climate, and geographic conditions. Furthermore, fixed effects at the agricultural district level are not co-linear to the weather and economic variables and because the weather variables are at the county level. Moreover, the weather variables vary over time while the agricultural districts fixed effects do not.

Figure 22: USDA NASS defined Agricultural Statistics Districts



The univariate Poisson distribution, denoted by $Poisson(y|\mu)$, for the number of occurrences of farmer suicide over a fixed exposure period (here, a year) has the probability mass function:

$$Pr(Y = y|\mu) = \frac{e^{-\mu}\mu^{y}}{y!}, \quad y = 0, 1, 2, \ldots \tag{16}$$

The exponential mean parameterization is $\mu = exp(\boldsymbol{x'\beta})$ to ensure that $\mu > 0$. The exponential mean parameterization is given by $E[y|x] = \mu = e^{(\boldsymbol{x'\beta})}$.

In the county-year panel data context, farmer suicide count in a county i in a year t

follows the multivariate Poisson distribution:

$$y_{it}|\boldsymbol{x_{it}}, \boldsymbol{\beta} \sim \text{Poisson}\Big(\exp(\boldsymbol{x'_{it}}\boldsymbol{\beta})\Big). \tag{17}$$

Given our assumptions about exogenous within-county variation and potential endogenous cross-sectional variation in the regressors, the number of occurrences of farmer suicide over a fixed exposure period (a year) in a county i has the probability mass function:

$$y_{it}|\boldsymbol{x_{it}}, \alpha_\iota \sim Poisson\Big(\alpha_\iota \exp(\boldsymbol{x'_{it}}\boldsymbol{\beta})\Big) \sim Poisson\Big(\exp(\ln \alpha_\iota + \boldsymbol{x'_{it}}\boldsymbol{\beta})\Big). \tag{18}$$

The exponential mean parameterization is given by:

$$E[y_{it}|\alpha_\iota, \boldsymbol{x_{it}}] = \mu_{it} = \exp(\ln \alpha_\iota + \boldsymbol{x'_{it}}\boldsymbol{\beta}). \tag{19}$$

In the context of our data, $i = 1, 2, 3, ..., 3037$, and $t = 1999, 2000, ..., 2017$. α_ι denotes fixed effects, i.e. the time-invariant value for each geographic (ASD) level ι.

Given the conditional mean assumption, Poisson maximum likelihood estimates represent the percentage change in the farmer suicide count from its mean caused by one unit change in the regressor. The average marginal effect of a unit change in a continuous regressor, x_j, is estimated by the proportional change of $E[y_{it}|\alpha_\iota, \boldsymbol{x_{it}}]$ by the amount of β_j, i.e.,

$$\frac{\partial E[y_{it}|\alpha_\iota, \boldsymbol{x_{it}}]}{\partial x_j} = \beta_j \exp(\ln \alpha_\iota + \boldsymbol{x'_{it}}\boldsymbol{\beta}) = \hat{\beta}_j \bar{y}_{it}, \tag{20}$$

where $\bar{y_{it}}$ is the mean of the outcome variable, i.e., mean of farmer suicide count.

This empirical model can test the two key hypotheses derived from the theoretical analysis: (i) harmful weather is positively associated with farmer suicide count, and (ii) bad economic conditions in the local agricultural economy are positively associated with farmer suicide count.

Specifications

If we take the log at both sides of the exponential mean parameterization equation, we have the following equation, where the independent variables and the agricultural district fixed effects are on the right-hand side.

$$\log\left(E[y_{it}|\alpha_\iota, \boldsymbol{x_{it}}]\right) = \log\left(\mu_{it}\right) = \log\alpha_\iota + \boldsymbol{x'_{it}\beta}, \tag{21}$$

where $\boldsymbol{x'_{it}\beta}$ includes weather variables (precipitation, cumulative degree days) and economic variables. Based on the dummy variables to denote animal- and crop-dominating counties, we develop two specifications to test the hypotheses: (i) A first specification involves the weather variables plus the interaction terms of the economic index and the crop- and animal-dominating dummy variables. (ii) A second specification involves running two separate regressions using two sub-samples—a crop-dominating counties sub-sample and an animal-dominating counties sub-sample. Specification (i) allows us to analyze the interaction effects, and specification (ii) separates the crop- and animal-dominating counties to avoid ambiguous effects of economic indexes due to some crops being inputs (feed) of animal production.

Interaction effects

$$
\begin{aligned}
&... + \gamma_C D_i^C + \gamma_A D_i^A + \beta_C I_{it}^C + \beta_A I_{it}^A \\
&\quad + \beta_{CC} I_{it}^C \times D_i^C + \beta_{AA} I_{it}^A \times D_i^A + \beta_{CA} I_{it}^C \times D_i^A + \beta_{AC} I_{it}^A \times D_i^C + ...
\end{aligned}
\tag{22}
$$

Equation (22) illustrates the economic part of the specification (i) with interaction effects, assuming the effect of the economic index on farmer suicide is heterogeneous across the counties in the three groups, i.e., crop-dominating counties, animal-dominating counties, and counties neither crop nor animal dominated. For example, the unique effect of crop index on farmer suicide is not limited to β_C but also depends on the value of β_{CC} and β_{CA}. β_C is interpreted as the base effect of crop index on farmer suicide only when D_i^C and D_i^A are both zero. The effect of crop index on farmer suicide in crop-dominating counties is measured by $\beta_C + \beta_{CC}$, the base effect plus the effect particular on crop-dominating counties when the indicator variable D_i^C turned on. The detailed effects are listed in table 18.

Table 18: The interaction effects of economic indexes on farmer suicide

Dominating type	D_i^C	D_i^A	Equation
Base	0	0	$\beta_C I_{it}^C + \beta_A I_{it}^A$
Crop-dominating	1	0	$\gamma_C + (\beta_C + \beta_{CC}) I_{it}^C + (\beta_A + \beta_{AC}) I_{it}^A$
Animal-dominating	0	1	$\gamma_A + (\beta_C + \beta_{CA}) I_{it}^C + (\beta_A + \beta_{AA}) I_{it}^A$

Two sub-samples

An alternative way to deal with the potential endogeneity problem is to run separate regressions of a sub-sample of crop-dominating counties and a sub-sample of animal-dominating counties. Based on the indicator variables D_i^C and D_i^A, we can easily select the two desired sub-samples. In the crop-dominating sub-sample, we include the crop index only. In the animal-dominating sub-sample, we include the animal index and feed index.

Sub-sample	Sample selection	Variables
Crop-dominating counties	$D_i^C = 1$	I_{it}^C
Animal-dominating counties	$D_i^A = 1$	I_{it}^A and I_{it}^F

In both specifications, we include two-year and three-year moving average economic index variables alternatively to the own-year economic index to test if prolonged adverse economic conditions impact farmer suicide differently than a single year of bad economic conditions.[17]

4.4 Results

We start with the Poisson fixed effects model including only weather variables and farm population (omitting the economic indexes) as the baseline regressions to set the stage for analysis of the full model. For robustness-check purposes, we developed various specifications with linear, quadratic, and cubic formats of precipitation and degree days, respectively. For data-scaling purposes, units of measurement in regression results tables were adjusted as follows: precipitation from millimeters to meters, degree days and growing degree days from one day to one thousand days, harmful degree days from one day to one hundred days.

Table 19 shows baseline regressions with precipitation specified in linear and quadratic forms and with degree days above 10 °C specified in linear, quadratic, and cubic formats respectively. All regressions include agricultural district fixed effects. Precipitation has a robust positive linear effect on farmer suicide. The effect of precipitation in regressions with

[17]Detailed definitions of the moving average indexes are listed in table 7.

Table 19: Baseline regressions: linear and quadratic precipitation and degree days above 10°C

	(1)	(2)	(3)	(4)	(5)	(6)
Joint Significance[a]				***	**	**
Extreme point (mm)				967.58	1052.24	1001.65
Precipitation (m)	0.254***	0.214**	0.212***	0.776**	0.564	0.607*
	(8.769e-02)	(8.398e-02)	(8.166e-02)	(3.625e-01)	(3.565e-01)	(3.280e-01)
Precipitation^2				-0.401	-0.268	-0.303
				(2.563e-01)	(2.566e-01)	(2.374e-01)
Joint Significance[b]		**	***		**	***
Extreme point(s) (days)		1586	1595,2863		1556	1590,2849
DD10	-0.191***	0.628*	7.944***	-0.188***	0.579	7.924***
	(6.135e-02)	(3.717e-01)	(1.228)	(6.094e-02)	(3.796e-01)	(1.244)
DD10^2		-0.198**	-3.878***		-0.186*	-3.882***
		(9.713e-02)	(5.896e-01)		(9.820e-02)	(5.957e-01)
DD10^3			0.580***			0.583***
			(9.030e-02)			(9.111e-02)
Farm Pop (000)	0.391***	0.392***	0.375***	0.393***	0.393***	0.377***
	(4.436e-02)	(4.625e-02)	(4.296e-02)	(4.457e-02)	(4.622e-02)	(4.291e-02)
Observations	56639					
Ag district F.E.	Y	Y	Y	Y	Y	Y
AIC	28178.66	28163.39	28082.84	28176.06	28163.40	28082.29
BIC	28205.49	28199.17	28127.56	28211.83	28208.13	28135.96

Note: Regular standard errors in parentheses for regression (1).
Clustered standard errors by Agricultural districts in parentheses for regressions (2) - (5).
* $p < .1$, ** $p < .05$, *** $p < .01$

[a] The joint significance row indicates the joint significance of three coefficients of the linear and quadratic terms of precipitation.
[b] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.

quadratic terms shows an inverted-U shape, where most of the data is located in the increasing portion of the curve. The result from the quadratic specification is consistent with the one in the linear format. The coefficients of precipitation squared are not significant in regressions (4), (5), and (6), although the linear and quadratic terms are jointly significant. These results support that it is sufficient to include the linear term of precipitation in regressions moving forward.

Coefficients of degree days above 10°C in cubic terms demonstrate better significance in both individual coefficients and joint significance compared to coefficients of DD10 in quadratic terms. The quadratic function of DD10 shows an inverted-U shape. The cubic function of DD10 yields a curve increasing to an extreme point, then decreasing to another extreme point, followed by the final increasing portion associated with the hottest weather. AIC and BIC denote Akaike's and Schwarz Bayesian Information Criterion for model selection, evaluating adjusted Mean Squared Error(MSE) with a penalty term.[18] The lower the value of AIC or BIC, the better the model fits. Based on AIC and BIC, regression (3) illustrates the best fit of the model. Thus, in the main results section, the specification with linear precipitation and cubic degree days is presented.

Table 20 shows an alternative version of table 19, where the degree days above 10°C is replaced by growing degree days between 10°C and 34°C and harmful degree days above 34°C. Similar to table 19 , table 20 reveals that precipitation in a linear format is sufficient to show the positive effect on farmer suicide. Growing degree days in quadratic function shows a U-shaped curve, indicating that cold weather is associated with increased farmer suicide and medium heat is associated with lower farmer suicide. The extreme heat, represented by harmful degree days (above 34°C), shows a positive and significant effect on farmer suicide. This finding is consistent with the cubic shape of degree days above 10°C found in regression (3) in table 19.

Two alternative regression result tables using degree days above 8°C (table 29), growing degree days between 8°C and 32°C, and harmful degree days above 32°C (table 30) can be found in the Appendix. Note that the coefficients of harmful degree days above 32°C in

[18]Given a model with k regressors and a constant and sample of size n, $AIC = n\log(MSE) + 2(k+2)$, and $BIC = n\log(MSE) + \log(n)(k+2)$.

Table 20: Baseline regressions: linear and quadratic precipitation with GDD between 10°C to 34°C and HDD above 34°C

	(1)	(2)	(3)	(4)	(5)	(6)
Joint Significance[a]				***	***	***
Extreme point (mm)				1067.57	1283.15	1155.56
Precipitation	0.365***	0.349***	0.315***	0.948***	0.716**	0.728**
	(8.514e-02)	(8.713e-02)	(8.230e-02)	(3.528e-01)	(3.553e-01)	(3.331e-01)
Precipitation^2				-0.444*	-0.279	-0.315
				(2.553e-01)	(2.578e-01)	(2.400e-01)
Joint Significance[b]		***	***		***	***
Extreme point(s) (days)		1533	1580,2924		1510	1573,2915
GDD10-34	-0.260***	0.828**	7.665***	-0.261***	0.779**	7.648***
	(6.087e-02)	(3.697e-01)	(1.296)	(6.109e-02)	(3.776e-01)	(1.314)
GDD10-34^2		-0.270***	-3.736***		-0.258***	-3.743***
		(9.651e-02)	(6.268e-01)		(9.760e-02)	(6.336e-01)
GDD10-34^3			0.553***			0.556***
			(9.638e-02)			(9.727e-02)
HDD34	0.442	0.590**	0.493*	0.465*	0.599**	0.503*
	(2.824e-01)	(2.834e-01)	(2.895e-01)	(2.824e-01)	(2.827e-01)	(2.882e-01)
Farm Pop (000)	0.392***	0.394***	0.378***	0.394***	0.395***	0.379***
	(4.313e-02)	(4.513e-02)	(4.190e-02)	(4.321e-02)	(4.505e-02)	(4.181e-02)
Observations	56639					
Ag district F.E.	Y	Y	Y	Y	Y	Y
AIC	28169.14	28142.00	28078.58	28165.52	28141.84	28077.82
BIC	28204.92	28186.72	28132.25	28210.24	28195.51	28140.43

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] The joint significance row indicates the joint significance of three coefficients of the linear and quadratic terms of precipitation.
[b] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of growing degree days between 10°C and 34°C.

table 4 are positive and not significant, unlike the results found in harmful degree days above 34°C. Since the cutting point on which degree the cumulative heat becomes harmful is controversial, we prefer to utilize total degree days as an explanatory variable, instead of separating degree days into growing degree days and harmful degree days to avoid arbitrary cut-off points, given the ambiguity in the literature as to where the break between GDD and

HDD should be set.

Table 21: Baseline regressions: with and without fixed effects

	(1)	(2)	(3)	(4)	(5)
Precipitation	0.084	0.212***	0.219**	0.349***	0.357***
	(6.998e-02)	(8.166e-02)	(9.309e-02)	(8.713e-02)	(9.024e-02)
Joint Significance[a]	***	***	***	***	***
Extreme point(s) (days)	1660,2867	1595,2863	1600,2854	1533	1552
DD10	6.795***	7.944***	8.094***		
	(7.760e-01)	(1.228)	(1.257)		
$DD10^2$	-3.232***	-3.878***	-3.948***		
	(3.670e-01)	(5.896e-01)	(6.018e-01)		
$DD10^3$	0.476***	0.580***	0.591***		
	(5.532e-02)	(9.030e-02)	(9.196e-02)		
GDD10-34				0.828**	0.829**
				(3.697e-01)	(3.767e-01)
GDD10-34^2				-0.270***	-0.267***
				(9.651e-02)	(9.735e-02)
HDD34				0.590**	0.594**
				(2.834e-01)	(2.876e-01)
Farm Pop (000)	0.410***	0.375***	0.385***	0.394***	0.403***
	(1.040e-02)	(4.296e-02)	(4.505e-02)	(4.513e-02)	(4.725e-02)
Constant	-7.581***				
	(5.182e-01)				
Observations	56639				
Ag district F.E.	N	Y	Y	Y	Y
Year F.E.	N	N	Y	N	Y
AIC	28718.25	28082.84	28026.04	28142.00	28088.49
BIC	28771.92	28127.56	28231.76	28186.72	28294.22

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.

Appropriate choice of fixed effects is worth discussing as they allow the model to control for time-invariant and/or temporal omitted variables. Table 21 shows a set of regressions with and without different fixed effects. Regression (1) does not include any fixed effects.

Regressions (2), (3), (4) and (5) include agricultural district fixed effects. Regressions (3) and (5) include year fixed effects in addition to the region fixed effects.

Agricultural district fixed effects are not colinear with explanatory variables. Fixed effects can remove potential omitted variable bias caused by missing or unknown time-varying characteristics. The regression coefficients in columns (2) and (4), with only agricultural district fixed effects, are very similar to the coefficients in columns (3) and (5). Thus, the model without year fixed effects is sufficient to infer associations between weather variables and farmer suicide count. The model specification with linear precipitation, cubic degree days, and economic indexes, with agricultural district fixed effects is used to present the main results.

Table 22 shows regressions with interaction effects between the crop- and animal-dominating county dummy variables and the economic index variables. Table 23 illustrates regressions separating the sample into two sub-samples of crop-dominating counties and animal-dominating counties. Several variations of specifications contain both agricultural district fixed effects and year fixed effects are reported in the robustness section.

Precipitation

Results suggest that farmers are more likely to commit suicide as the precipitation levels increase in general. For example, precipitation has a statistically significant coefficient of 0.256 in regression (1) in table 22, indicating, for example, that a 100 mm raise in cumulative precipitation causes farmer suicide count to increase by 2.56%. This result is robust to alternative specifications.

Farmers' irrigation activities possibly distort the effect of precipitation on farmer sui-

Table 22: Regression results: interaction effects of economic indexes and dominating dummy variables including agricultural district fixed effects

		(1)	(2)	(3)	(4)	(5)	(6)
Index		3-yr moving averag		2-yr moving average		Own year indices	
Counties		All	Non-irrigated	All	Non-irrigated	All	Non-irrigated
Precipitation		0.256***	0.029	0.237***	0.020	0.209**	-0.009
		(9.106e-02)	(1.407e-01)	(8.481e-02)	(1.405e-01)	(8.291e-02)	(1.366e-01)
Joint Significance[a]		***	***	***	***	***	***
DD10		7.652***	9.981***	8.033***	10.375***	7.665***	10.935***
		(1.326)	(1.494)	(1.299)	(1.488)	(1.250)	(1.393)
$DD10^2$		-3.730***	-4.700***	-3.911***	-4.885***	-3.754***	-5.152***
		(6.399e-01)	(7.478e-01)	(6.246e-01)	(7.480e-01)	(5.999e-01)	(7.026e-01)
$DD10^3$		0.557***	0.683***	0.585***	0.711***	0.564***	0.752***
		(9.839e-02)	(1.169e-01)	(9.582e-02)	(1.176e-01)	(9.174e-02)	(1.109e-01)
Farm Pop (000)		0.388***	0.516***	0.388***	0.515***	0.383***	0.510***
		(4.756e-02)	(6.099e-02)	(4.611e-02)	(6.245e-02)	(4.479e-02)	(6.137e-02)
$D_C = 1$	γ_C	0.100	0.108	0.095	0.107	0.107	0.129*
		(7.099e-02)	(8.148e-02)	(6.677e-02)	(7.716e-02)	(6.669e-02)	(7.729e-02)
$D_A = 1$	γ_A	0.014	-0.027	0.007	-0.023	0.023	0.004
		(9.213e-02)	(7.117e-02)	(8.401e-02)	(6.280e-02)	(8.421e-02)	(6.491e-02)
Crop Index	β_C	0.303	0.286	0.129	0.088	-0.043	-0.167
		(2.467e-01)	(3.055e-01)	(2.411e-01)	(2.990e-01)	(2.037e-01)	(2.689e-01)
Animal Index	β_A	0.010	0.171	0.187	0.319	0.437**	0.657**
		(3.244e-01)	(4.507e-01)	(2.433e-01)	(3.722e-01)	(1.740e-01)	(2.803e-01)
Crop Idx $\times D_C = 1$	β_{CC}	-0.532*	-0.560*	-0.328	-0.302	-0.075	0.063
		(2.783e-01)	(3.245e-01)	(2.711e-01)	(3.154e-01)	(2.210e-01)	(2.652e-01)
Animal Idx $\times D_A = 1$	β_{AA}	-0.801**	-1.261**	-0.750***	-1.030**	-0.531**	-0.805**
		(3.489e-01)	(4.956e-01)	(2.794e-01)	(4.203e-01)	(2.272e-01)	(3.634e-01)
Crop Idx $\times D_A = 1$	β_{CA}	-0.184	-0.199	-0.100	-0.077	-0.083	-0.003
		(2.838e-01)	(3.416e-01)	(2.676e-01)	(3.179e-01)	(2.227e-01)	(2.866e-01)
Animal Idx $\times D_C = 1$	β_{AC}	-0.452	-0.609	-0.517	-0.691	-0.619***	-0.974***
		(4.319e-01)	(6.082e-01)	(3.468e-01)	(5.182e-01)	(2.208e-01)	(3.483e-01)
Observations		50507	38573	53478	40842	56449	43111
AIC		24994.64	18882.40	26566.57	20067.81	28019.37	21097.33
BIC		25109.42	18993.68	26682.10	20179.84	28135.61	21210.06
Crop: $(\beta_C + \beta_{CC})I_C$		-0.229*	-0.274*	-0.199	-0.214	-0.118	-0.104
Crop: $(\beta_A + \beta_{AC})I_A$		-0.442	-0.438	-0.33	-0.372	-0.182***	-0.317***
Animal: $(\beta_C + \beta_{CA})I_C$		0.119	0.087	0.029	0.011	-0.126	-0.17
Animal: $(\beta_A + \beta_{AA})I_A$		-0.791**	-1.09**	-0.563***	-0.711**	-0.094**	-0.148**

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.

cide. Irrigated agriculture is less susceptible to fluctuations in precipitation than rainfed agriculture. Based on the county-level irrigation information data retrieved from USDA NASS, we created an indicator variable for each county to indicate if a county is an irrigated

Table 23: Regression results: two sub-samples of crop- and animal-dominating counties including agricultural district fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Index	3-yr moving average		2-yr moving average		Own year indices	
Dominating	Crop	Animal	Crop	Animal	Crop	Animal
Precipitation	0.215	0.371***	0.235*	0.328***	0.211	0.299**
	(1.344e-01)	(1.094e-01)	(1.396e-01)	(1.126e-01)	(1.350e-01)	(1.181e-01)
Joint Significance[a]	***	***	***	***	***	***
DD10	9.631***	5.847***	10.307***	6.289***	11.022***	5.337***
	(2.580)	(1.420)	(2.613)	(1.361)	(2.399)	(1.301)
$DD10^2$	-4.330***	-2.987***	-4.683***	-3.204***	-5.042***	-2.782***
	(1.274)	(6.640e-01)	(1.284)	(6.387e-01)	(1.188)	(6.109e-01)
$DD10^3$	0.593***	0.461***	0.652***	0.496***	0.710***	0.437***
	(2.003e-01)	(1.003e-01)	(2.002e-01)	(9.767e-02)	(1.866e-01)	(9.295e-02)
Farm Pop (000)	0.515***	0.389***	0.518***	0.389***	0.494***	0.382***
	(8.042e-02)	(4.244e-02)	(8.299e-02)	(4.035e-02)	(8.595e-02)	(4.151e-02)
Crop Index	-0.301***		-0.246**		-0.152*	
	(1.049e-01)		(9.796e-02)		(8.870e-02)	
Animal Index		-0.807***		-0.557***		-0.070
		(1.739e-01)		(1.772e-01)		(1.440e-01)
Feed Index		0.150		0.049		-0.126
		(1.327e-01)		(1.192e-01)		(1.017e-01)
Observations	19499	23205	20646	24570	21793	25935
AIC	9722.49	11171.14	10356.77	11881.48	10951.46	12540.01
BIC	9769.76	11227.51	10404.38	11938.25	10999.39	12597.15

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

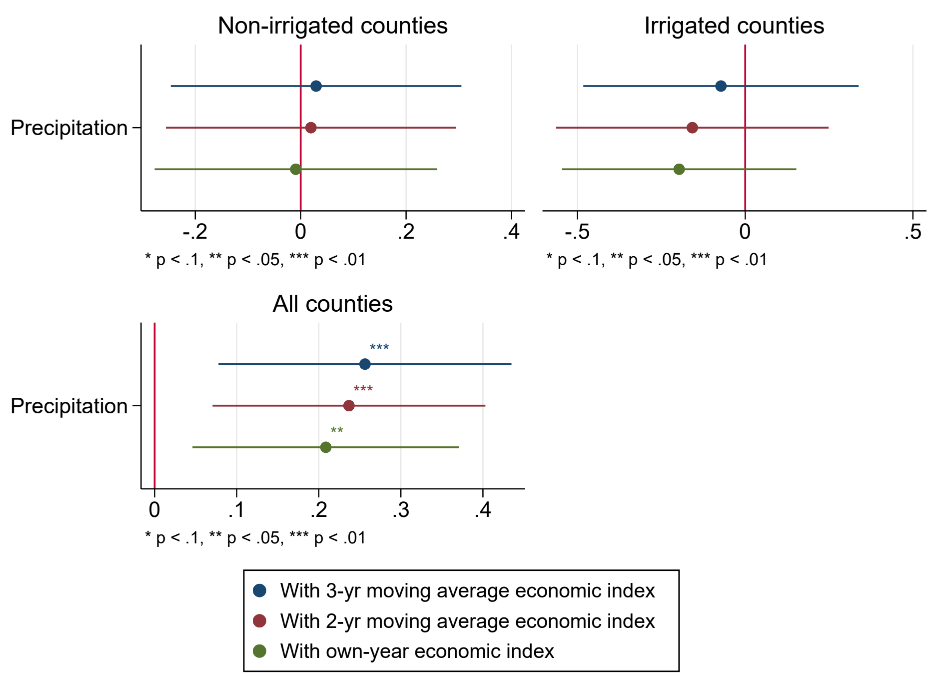
[a] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.

county or non-irrigated county. A county was classified into a non-irrigated county group if this county had no irrigation information in the census years 2007, 2012, and 2017.

Summary statistics of a comparison of counties with and without irrigation can be found in table 31 in the Appendix. Precipitation levels in the irrigated counties, on average, are lower than the average in non-irrigated counties. Extreme heat accumulates more, on average, in irrigated counties compared to non-irrigated counties.

To test the hypothesis that precipitation is a causal factor in farmer suicides in counties with predominantly rainfed agriculture, we created a sub-sample of the data to include only the non-irrigated counties, which on average are cooler and more humid than irrigated counties. Regressions (2), (4), and (6) in table 22 show that, in non-irrigated counties, the coefficients on precipitation are positive but not statistically significant.

Figure 23: The coefficients plot of precipitation in table 22



Note: Horizontal lines represent 95 percent confidence intervals.

Figure 23 compares the coefficients of precipitation from regressions only including non-irrigated counties (displayed on the top left-hand side) and the coefficients from regressions only including irrigated counties (displayed on the top right-hand side),[19] and coefficients from regressions including all counties (displayed on the bottom left). The horizontal lines

[19]Detailed regression results table (table 32) of irrigated counties is displayed in the Appendix.

indicate 95% confidence intervals. Precipitation level is not statistically related to farmer suicide in rainfed counties. This finding is consistent with studies of the effect of precipitation on the suicide among the general population (Lambert et al., 2003; Ajdacic-Gross et al., 2007; Ruuhela et al., 2009; Carleton, 2017).

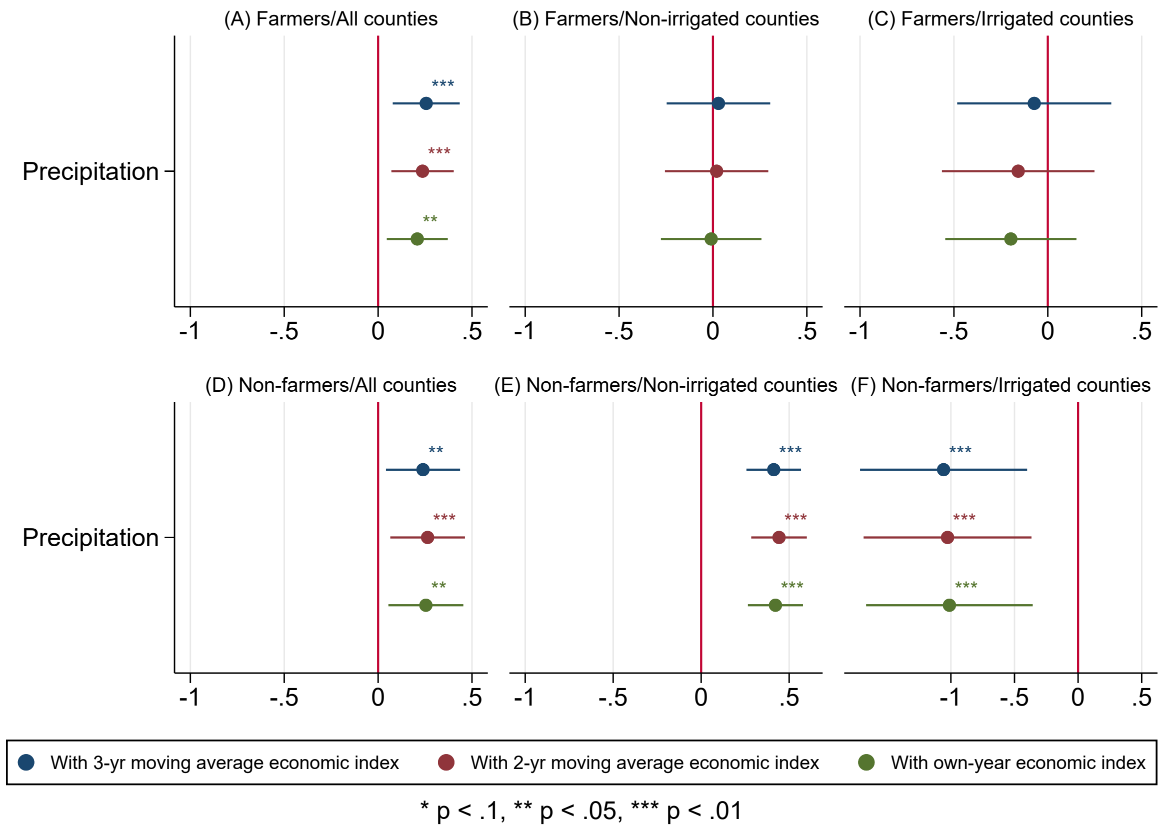
The positive effect found in regressions including all counties indicates a general precipitation effect on farmer suicide, which may be due to both the psychological effects of rainfall and cloudy, gloomy days, and the effects through the farming channel. In order to further decompose this effect into two parts, we later in the robustness section compare farmer suicide regressions with non-farmer suicide regressions, which partially reveal the psychological effects of precipitation on suicide.

Figure 24 shows comparisons of the coefficients plot of precipitation in farmer suicide count regressions and non-farmer suicide count regressions. The value of each coefficient is displayed as a dot with its significance level labeled on the top. The line represents the 95% confidence interval of the coefficient.

Precipitation's effect on farmer suicide can comprise both a psychological effect and an effect through the farming channel, where precipitation level affects crop growth, yield, and farm profit. Literature regarding precipitation and suicide among the general population has established that the sign of the effect depends on the baseline precipitation level of locations. For example, in drought areas, studies usually find precipitation reduces suicide rates (Deisenhammer et al., 2003; Nicholls et al., 2006; Hanigan et al., 2012). In contrast, more precipitation increases suicide rates in tropical areas where the baseline precipitation level is already high (Tsai, 2010).

In figure 24, the bottom three coefficients plots demonstrate the effect of precipitation

Figure 24: Coefficients plot of precipitation: farmer and non-farmer suicide comparison



Note: Horizontal lines represent 95 percent confidence intervals.

on non-farmer suicide, which we use as a rough proxy of the psychological effect on suicide among the general population. The average precipitation level is relatively high in non-irrigated counties and low in irrigated counties: our sample mean is 724 mm and 367 mm in the non-irrigated sub-sample and irrigated sub-sample, respectively. Thus, we expect to see a positive effect of precipitation on non-farmer suicide in wet areas and a negative effect in dry areas.

Coefficients of precipitation presented in subplots (E) and (F) in figure 24 illustrate a consistent story with findings in the prior literature. Precipitation is positively associated with non-farmer suicide in non-irrigated counties where the baseline average precipitation level is high, and negatively associated with non-farmer suicide in irrigated counties where the baseline average precipitation level is low, although the effect is not always statistically significant.

The understanding of the psychological effect of precipitation on suicide among non-farmers sets a stage for decomposing the total effect found in the regressions of farmer suicide, displayed on the top row in figure 24. To illustrate the process more clearly, table 24 summarizes the signs of the precipitation effect in different groups. Given the assumption that the total effect comprises a psychological effect and a farming effect, we can infer the sign of precipitation effect through the farming channel by "subtracting" the psychological effect from the total effect.

Table 24: Precipitation effect on suicide among farmers and non-farmers

Precipitation effect	All counties	Non-irrigated counties	Irrigated counties
Farmer suicide (Total effect)	$+^{***}$	0	$-$
Non-farmer suicide (Psychological effect)	$+^{**}$	$+^{***}$	$-^{***}$
Effect through farming channel			
(Weak inference)	0	$-$	0
(Strong inference)	$+$	$-$	$+$

In non-irrigated counties, the total effect of precipitation on farmer suicide is very small and positive but not significant. Living in areas with high rainfall, it is reasonable to assume that precipitation generally does not significantly affect farming in terms of crop growth. Given the positive and significant psychological effect and non-significant total effect, a weak inference can be made that the effect of precipitation through farming on suicide is negative to offset the positive and significant psychological effect. Schlenker and Roberts

(2009) find that precipitation has a statistically significant inverted-U shape on crop yield, with a yield-maximizing level of 635 mm for corn and 691 mm for soybeans in non-irrigated counties, near the average precipitation for non-irrigated counties in my data.

In irrigated counties, the total effect of precipitation on farmer suicide is negative and not significant. Without irrigation systems, precipitation should be positively associated with crop growth in drought areas. However, farmers adapt to drought environments by introducing irrigation systems. For example, Schlenker and Roberts (2009) find that precipitation is not statistically significant for cotton yields, as 58% of the crop is irrigated. Taking irrigation into account, it is appropriate to assume that precipitation should have little impact on farming in dry areas. Under a stronger inference, precipitation on top of well-irrigated fields can negatively impact crop growth and harvesting in some cases. A negative and significant psychological effect but a non-significant negative total effect may suggest that a small positive farming effect of precipitation offsets somewhat the significant negative psychological effect.

Degree days

Based on the results of exploratory regression models discussed previously, we use a third-order polynomial to fit farmer suicide count to degree days. Tables 22 and 23 show twelve sets of three coefficients associated with degree days above 10 °C, where each set of three represents the first-, second-, and the third-order coefficient of the cubic expression. For example, in regression (1) in table 22, the three coefficients of degree days represent $7.652DD_{10} - 3.73{DD_{10}}^2 + 0.557{DD_{10}}^3$.

Figure 25 shows how predicted farmer suicide count responds to degree days as its value goes up, holding all other variables constant at their mean values relative to a default baseline agricultural district. The cubic curves on the left side are the results in table 22 and the ones on the right side are from table 23. Note that the unit of degree days on the x-axis has been adjusted from one degree day to one thousand degree days. The y-axis represents the predicted mean farmer suicide count in a county in a year. Dashed lines represent 95 percent confidence bounds.

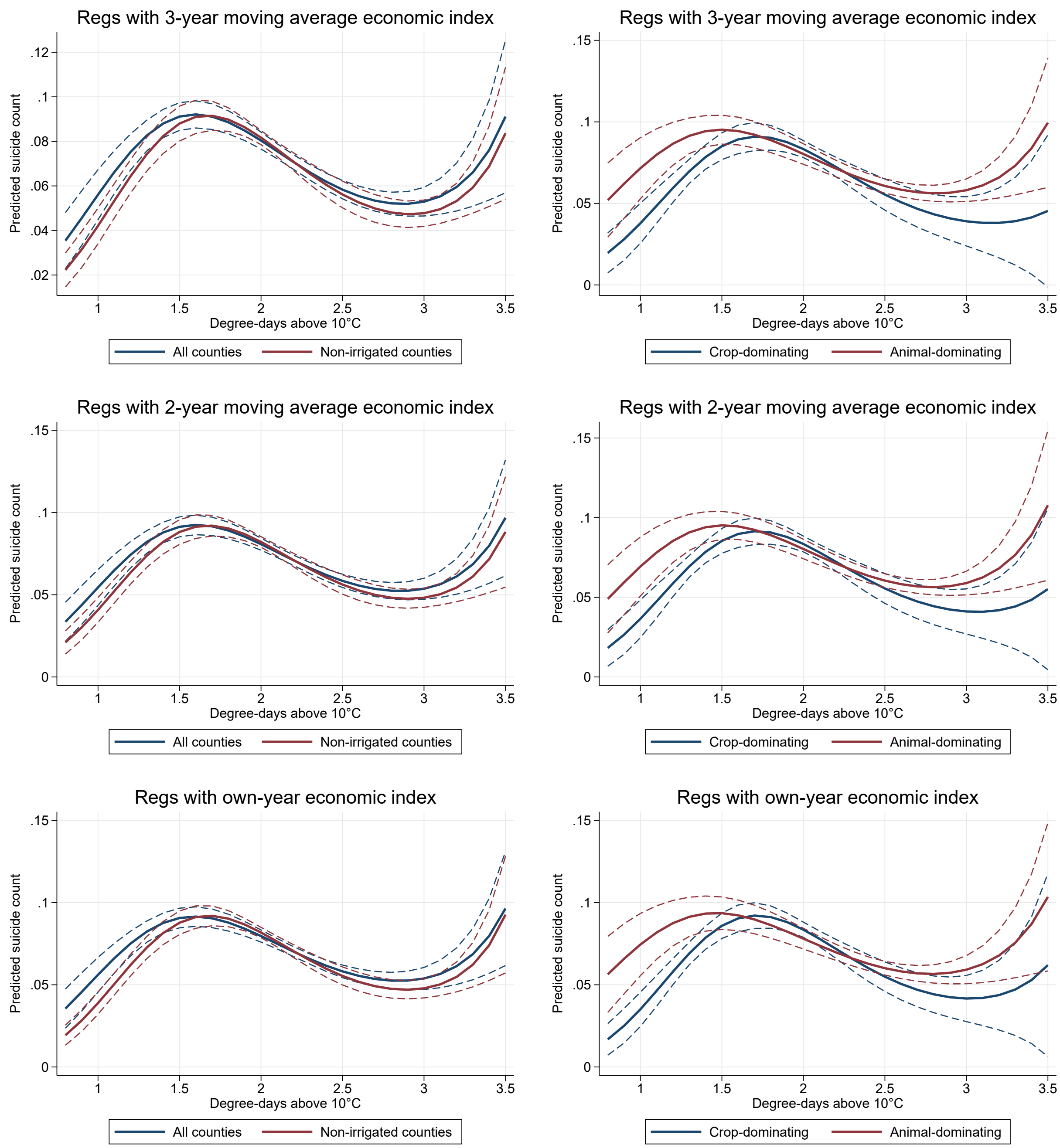
The cubic function has two extreme points. The vertical dashed lines in figure 26 identify the values of the extreme points with their percentile in the degree-day distribution indicated in parenthesis. To better understand the distribution of degree days, figure 26 shows the cubic curves in regression (1) and (2) from table 22 in comparison with a histogram of degree days above 10°C (DD10), truncated in the range between 0.8 to 3.5 (in 1000 degree days) on the x-axis. The 5^{th} percentile of the DD10 is close to 1000-degree days.

There are very little data located at the region of low degree days values. Thus, the increasing portion at the low DD10 region is likely due to the curve fitting the cubic shape. To further validate this point, we made a coefficients plot for degree days, showing the value of coefficients and their 95% confidence intervals in figure 27.

The first power coefficient dominates the shape of the cubic curve at small degree days values. Its 95% confidence interval range is relatively wide compared to the confidence intervals of quadratic and cubic term coefficients. This further supports the idea that the increasing part of the curve is more to fit the cubic shape than to indicate a statistically significant causal relationship between degree days and farmer suicide in this portion of the curve.

Most of the data are located between the two extreme points, where the curve is de-

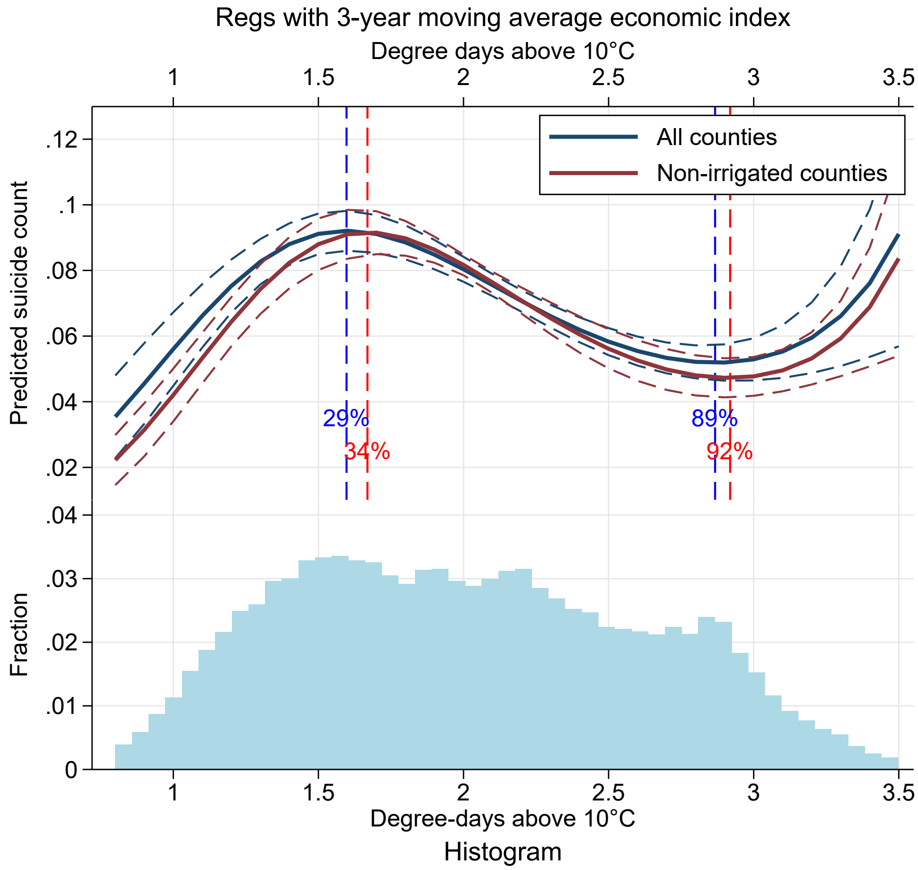
Figure 25: Predicted farmer suicide count responding to degree days, results from table 22 (left) and table 23 (right)



Note: Dashed lines represent 95 percent confidence bounds.

creasing. Thus, the impact of degree days on farmer suicide is negative at low to medium degree days levels. Moderate heat accumulation represented by growing degree days is ben-

Figure 26: Predicted farmer suicide count as a cubic function of degree days from regression (1) and (2) in table 22 and histogram of degree days sharing the same x-axis

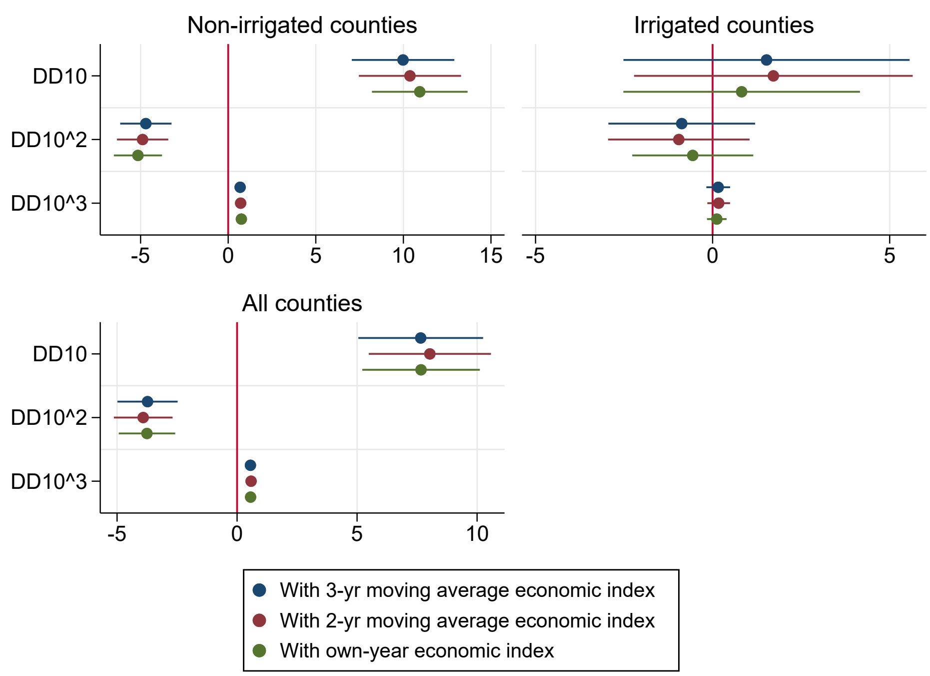


Note: Dashed curves represent 95 percent confidence bounds of the cubic margin plots. Dashed vertical lines show the percentiles of degree days at the extreme points.

eficial as it promotes plant growth (Ritchie & Nesmith, 1991; Schlenker et al., 2006; Roberts & Schlenker, 2011). Warmer temperatures are beneficial for farmers over a considerable range of temperature data.

High levels of degree days might be positively associated with an increased rate of farmer suicide. Farmer suicide count increases at an increasing rate when degree days pass a certain high level (for example, at about its 89 percentile), as shown in figure 26, suggesting that very high temperatures may be associated with elevated farmer suicide due to the

Figure 27: Coefficients plot of degree days in table 22



Note: Horizontal lines represent 95 percent confidence intervals.

impacts of extreme heat on crops and animals, the effect of extreme heat on farmers' physical and mental health, or both. However, most of the increasing portion of the function is outside the range of the data. An alternative specification involving growing degree days and harmful degree days produces a positive and significant effect of harmful degree days above 34°C on farmer suicide. However, the same finding is not found in regressions with harmful degree days above 32°C, suggesting that it is only the most extreme heat that impacts farmer suicide.[20]

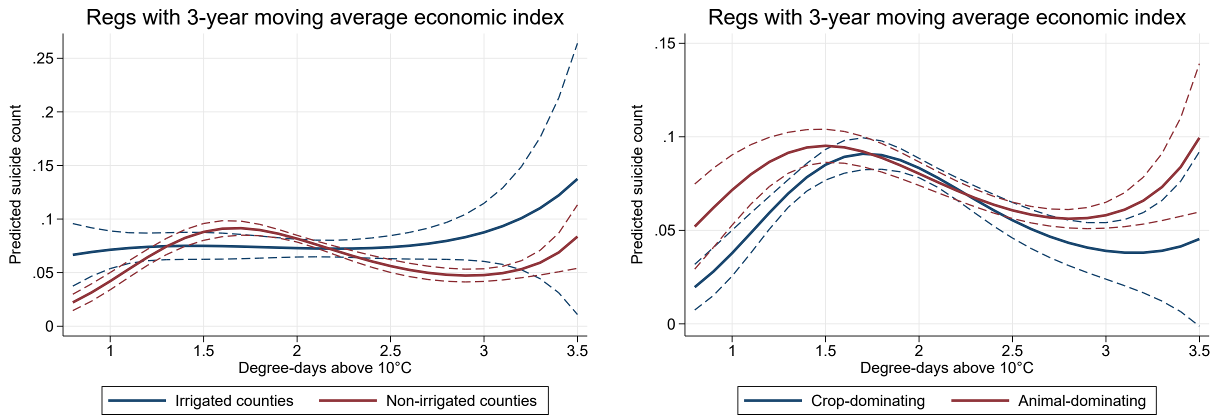
Thus, there is at best weak evidence that high heat accumulation is one of the factors of farmer suicide, which poses a challenge of the conclusion of Burke et al. (2018), as farming, among occupation types, is one of the most vulnerable occupations to extreme heat conditions.[21] Farmers work mainly outdoors where they are exposed to extreme heat, and their incomes are impacted through the effects of heat on crop and animal production.

Studying the split sample of crop-dominating and animal-dominating counties, it seems clear that there is no positive effect of high degree days on suicide for crop farmers. As noted, the hottest areas for crop production generally have irrigated agriculture, giving farmers the ability to mitigate extreme heat through crop watering. Figure 28 compares predicted farmer suicide count responding to increasing degree days in non-irrigated counties with irrigated counties. Noticeably, the curve of irrigated counties is nearly flat, indicating no effect of degree days on farmer suicide when irrigation systems are applied. This is consistent with our finding in crop-dominating counties (right-hand side of figure 28, where the curve is relatively flat through the range of hot temperatures. To the extent that cropland is irrigated, farmers

[20]Detailed regression result can be found in the Appendix in table 33 and table34.

[21](Burke et al., 2018) find that high temperatures are associated with higher rates of suicide among the general population.

Figure 28: Sub-sample analysis: Predicted farmer suicide and degree days above 10°C in irrigated and non-irrigated counties and in crop-dominating and animal-dominating counties



Note: The joint significance of the three cubic terms of degree days in the regression of irrigated counties is not significant. The individual coefficients are not statistically significant either.
Dashed lines represent 95 percent confidence bounds.

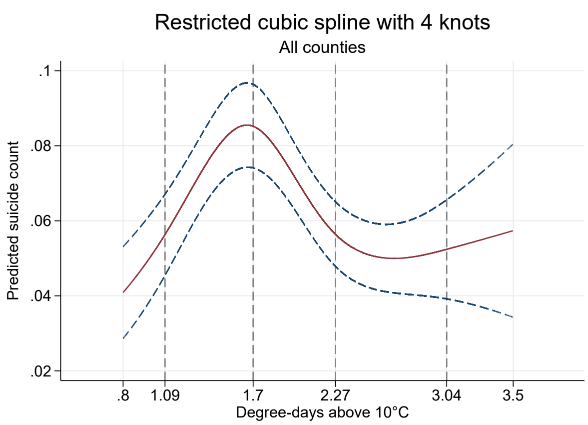
are relatively able to adapt to extreme heat.

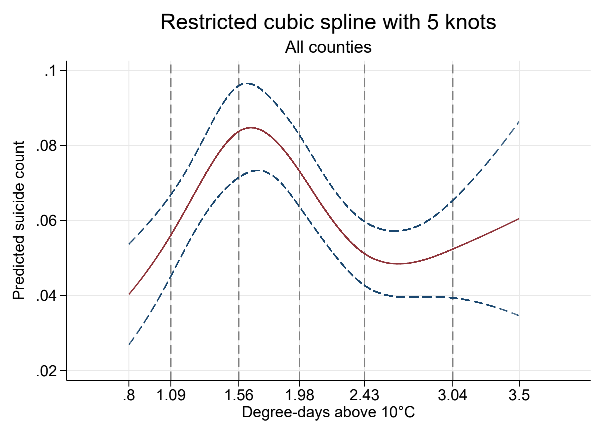
The impact of extreme heat on the health and mortality of farm animals has been studied extensively (Dantzer & Mormède, 1983; Altan et al., 2003; Lara & Rostagno, 2013; Sejian et al., 2018; Bernabucci, 2019). Heat is a significant stressor for farm animals and stressed animals are less productive (Lara & Rostagno, 2013). For example, extreme heat reduces milk yields and milk quality, meat production and fertility (Sejian et al., 2018). Extreme heat can cause death among farm animals. It is likely more impactful both mentally and financially for animal farmers to experience the loss of animals compared to crop farmers experiencing crop failures caused by extreme heat. Crop farming mostly follows an annual cycle, whereas the animal agricultural cycle is much longer. For example, the productive lifespan of an average cow from birth to death is between 4.5 to 6 years in most developed dairy industries (De Vries & Marcondes, 2020). Animal farmers are the stewards of their animals and fully responsible for their well-being. The psychological impact of seeing farm animals suffer or die in extreme temperatures could be quite devastating.

In order to check the robustness of this result, we use spline and restricted cubic spline functions to estimate the relationship between farmer suicide count and degree days above 10°C. This model uses variables containing a linear spline or a restricted cubic spline of degree days as one of the explanatory variables in the Poisson regression with agricultural district fixed effects, including 3-year moving average indexes.

Figure 29 shows the predicted farmer suicide count in response to increasing degree days estimated by a restricted cubic spline with four knots (left) and five knots (right). The vertical axis shows the predicted farmer suicide count. The locations of the knots are determined by the percentiles recommended by Harrell (2001). For four knots, the percentiles are 5, 35, 65, and 95. For five knots, the percentiles are 5, 27.5, 50, 72.5, and 95. The vertical dashed lines present the corresponding degree days values of the knots.

Figure 29: Restricted cubic spline regression margin plots

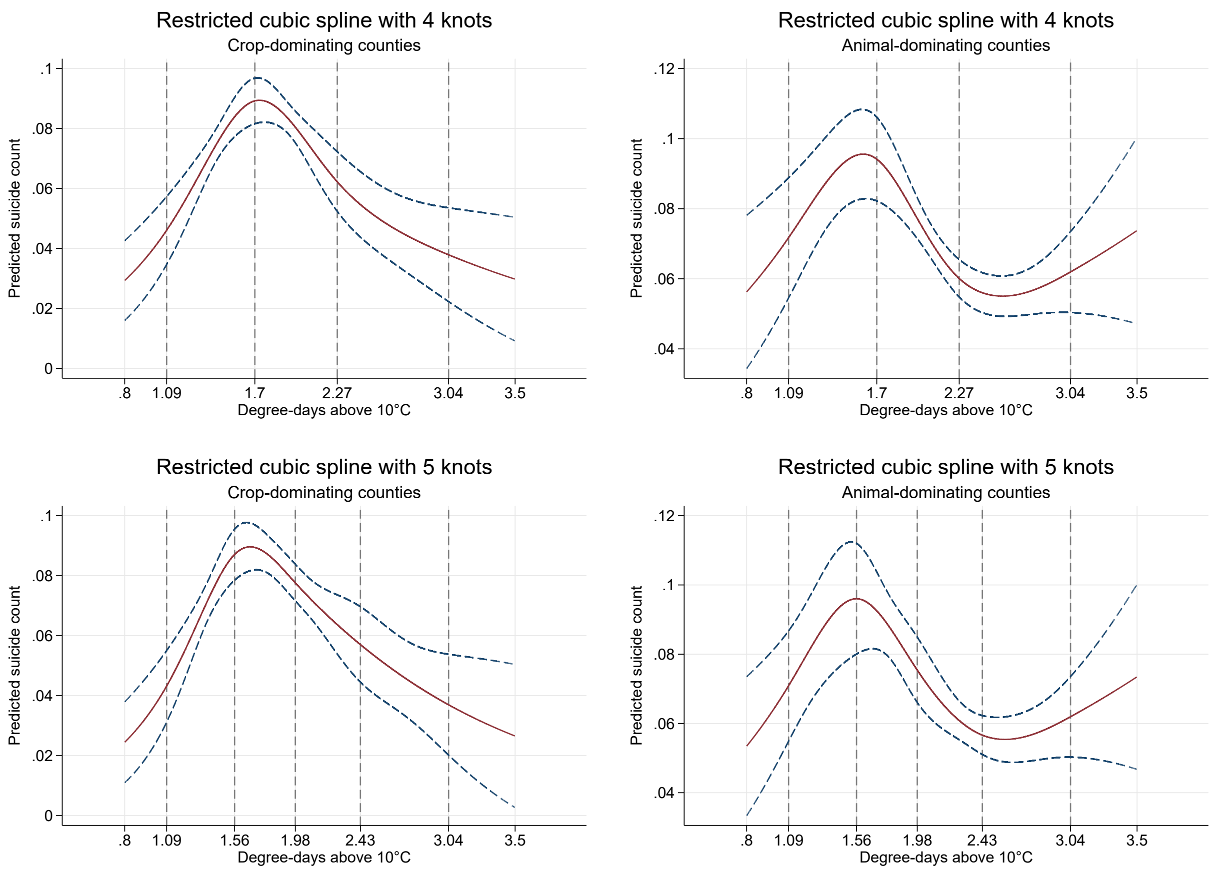




Note: Both figures show the margins plot from regressions with interaction effects of 3-year moving average economic indexes and dominating dummy variables including agricultural district fixed effects.
Dashed lines represent 95 percent confidence bounds.

The shape of the predicted farmer suicide count curve using a restricted cubic spline with four knots and five knots is robust. Predicted farmer suicide count decreases at medium degree days range and rises as cumulative heat increases at high degree days levels. This conclusion is consistent with the results from the Poisson fixed effects regressions and is also robust to the alternative number of knots.

Figure 30: Restricted cubic spline regression margin plots by dominating counties



Note: Both figures show the margins plot from regressions with two sub-samples with 3-year moving average economic indexes including agricultural district fixed effects.
Dashed lines represent 95 percent confidence bounds.

Based on the results from various regression analyses, we conclude that rising degree days in the growing season for low and moderate values have a negative impact on farmer suicide. The highest values of degree days seem to be associated with increasing farmer suicide rates, but the effect is estimated very imprecisely in the full sample, as the confidence intervals in figures 29 and 30 illustrate. The effect of extreme heat, however, is stronger and clearer for animal-dominating counties than for crop-dominating counties.

Economic Index

Table 22 lists the coefficients on indexes of the specification with interaction effects. The coefficient of D_A, denoted by γ_A in table 18, is positive and statistically significant in all six regressions, which indicates that animal-dominating counties, in general, are at higher risk of farmer suicide compared to non-animal-dominating counties. γ_C is positive but not statistically significant. Thus, there is no such effect in crop-dominating counties relative to nondominant counties.

Based on the equation in Table 18, the marginal effect of crop index on farmers in crop-dominating counties is $\beta_C + \beta_{CC}$, which is negative and statistically significant at the 90% confidence level ($p < 0.1$) for the three-year moving average crop index. For instance, the marginal effect in regression (1) equals $\beta_C + \beta_{CC} = 0.303 - 0.532 = -0.229$, which indicates that if the three-year moving average crop index increases by 0.1 unit, i.e., the weighted real crop prices go up by 10% from their historical means,[22] farmer suicide count in the crop-dominating counties decreases by 2.29%. This marginal effect is consistent if we only include non-irrigated counties in the sample (2.74%).

The marginal effect of two-year average and own-year crop index on farmer suicide in crop-dominating counties is negative and insignificant. This implies that a single year, or even two years, of good or bad crop prices does not affect farmer suicide. Instead, a prolonged

[22] Note that the one unit increase in crop index is not equivalent to 1% price increase of a single crop price. It's the overall weighted price increase of the selected five crops. For example, if a county produces an equal amount of corn, soybean, wheat, hay, and grape in sales (which gives each crop the same weight as $\frac{1}{5}$), and for each crop, when the price increases by 1%, 2%, 3%, 4% and 5% respectively, the weighted crop index increases by 3%: $\frac{1}{5} \times (1\% + 2\% + 3\% + 4\% + 5\%) = 3\%$.

period of good crop economic conditions decrease farmer suicide count in crop-dominating counties. Chronic bad crop economy conditions, conversely, are associated with increased farmer suicide in crop-dominating counties.

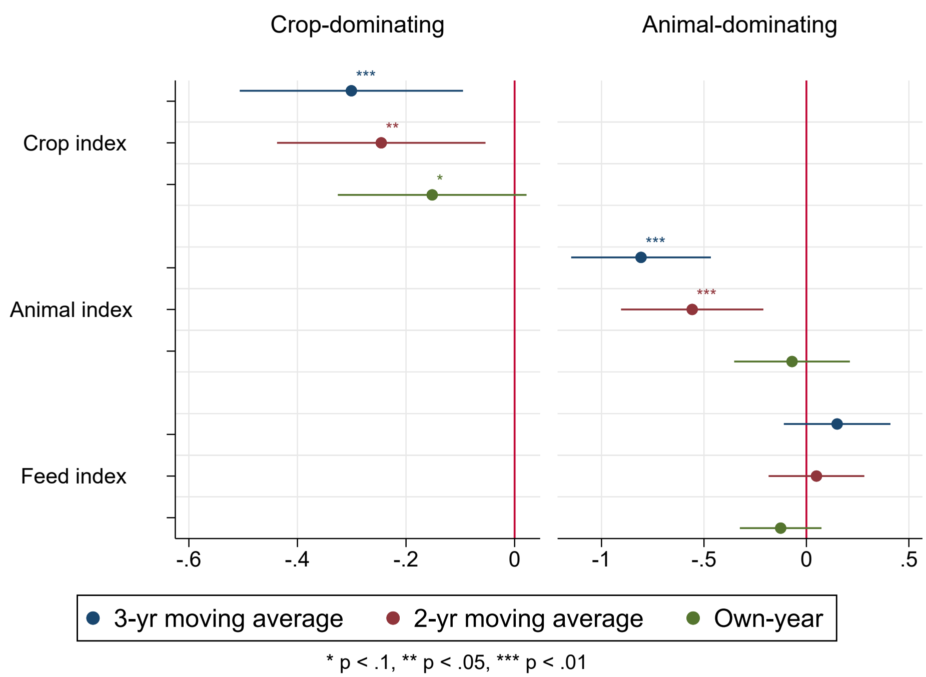
Similarly, the marginal effect of the animal index on farmer suicide count in animal-dominating counties is negative. For example, in regression (1) the marginal effect of three-year moving average animal index is $\beta_A + \beta_{AA} = 0.01 - 0.801 = -0.791$. A 0.1 unit increase in the animal economic index (prices of animal products on average go up by 10% from the historical mean) reduces the farmer suicide count in animal-dominating counties by 7.91%. In non-irrigated animal-dominating counties, this effect is even higher (10.9% at 95% significance level). The effect of two-year moving average and own-year animal index is smaller compared to the effect of three-year moving average animal index on farmer suicide count in animal-dominating counties and is statistically significant at 95% and 99% level, respectively. Conversely, low prices of animal products for several years are associated with elevated farmer suicide count. This result reinforces our finding that chronic poor economic conditions induce farmer suicide, especially in non-irrigated areas.

The bottom of table 22 also reports the interaction effect of the crop-dominating county dummy variable with the animal economic index and the animal-dominating county dummy variable with crop economic index. The higher animal index has no significant effect on farmer suicide count for crop-dominating counties, denoted by $\beta_A + \beta_{AC}$, except for the specification with own-year economic indexes.

The crop index represents an index of animal feed costs to some extent since four out of the five crops can be used as livestock feed. Thus, $\beta_C + \beta_{CA}$ measures the effect of feed costs on farmers in animal-dominating counties, with higher feed costs associated with lower profits in animal production. However, none of the coefficients is statistically significant. One possible reason is that crop farmers living in animal-dominating counties benefit from the high crop index, which offsets the negative effect of the crop index on animal farmers.

The results of economic indexes are robust to alternative specifications with split crop- and animal-dominating sub-samples. Figure 31 provides a coefficients plot of the three index variables in the regressions. Crop-dominating counties sub-sample regressions, including crop index only, are located on the left side of the figure. Animal index and feed index are included in the animal-dominating counties sub-sample regressions, displayed on the right side. We also incorporate three-year moving average, two-year moving average, and own-year versions for each economic index using the same calculations as in table 7.

Figure 31: Coefficients plot of economic indexes in table 23



Note: Horizontal lines represent 95 percent confidence intervals.

The coefficients plot of crop index in blue, red, and green, respectively, represents the coefficient of the crop index in regressions (1), (3), and (5). The impact of three-year moving average crop index is the strongest, -3.01% on farmer suicide count in crop-dominating subsample associated with 10% increase in crop prices, at the similar level as the effect estimated previously in table 22 (-2.29%). As we take into account fewer past periods index variation, this effect becomes smaller and less significant. The impact estimated by the own-year crop index is not statistically significant.

Results for the animal index in animal-dominating counties are similar. A 10% increase in the prices of animal products reduces farmer suicide count in animal-dominating counties by 8.07% (very close to -7.91% in table 22). The coefficient of the own-year animal index is not significant. Similarly, none of the feed index coefficients is statistically significant.

The results, again, suggest that a single year of low input and output prices does not impact farmer suicide. Rather, it is prolonged poor economic conditions of multiple years duration that appear to increase farmer suicide rates, a conclusion that is robust to alternative model specifications, as I show in the subsequent section. Farms in the U.S. are often passed along throughout multiple generations. The multi-generational farm owner bears additional pressure when operating their farms in a risky and volatile business environment. If one of the multi-generational farm owners loses the family business due to successive years of poor income, stress and self-blame emotions may exacerbate hopelessness which could lead to suicide.

4.5 Robustness Check

In this section, we present some alternative specifications of the regressions to show the robustness of the results. We relax the assumption of the exogeneity for within-county variations. Thus, year fixed effects are presented in the following alternative specifications. Table 25 and table 26 present the specifications including agricultural district fixed effects and year fixed effects, keeping other variables unchanged.

The specifications with interaction effects are located on the left side of figure 32, where the three sub-figures show the coefficients plots of regressions including three-year moving average, two-year moving average, and own-year indexes, respectively, from top to bottom. Symmetrically, the three sub-figures located on the right side represent the year fixed effects regressions in two sub-samples.

There is very little difference in year fixed effects between all counties sample and non-irrigated counties sample. Although the base year is different, the year fixed effects are quite consistent across the three specifications including own year, two-year, and three-year moving average economic indexes. Most of the year fixed effect coefficients are not statistically significant. Exceptions are 2001 and 2016, which have negative and statistically significant coefficients, indicating that the average farmer suicide count was low during these two years. The story is similar to the two sub-samples specifications.

Adding year fixed effects causes the coefficients of some economic indexes to lose statistical significance. For example, figure 33 shows the coefficients plot of economic indexes in the regressions of the two sub-sample specifications. The three- and two-year animal economic indexes continue to have negative coefficients but are not statistically significant.

Table 25: Regression results: interaction effects of economic indexes and dominating dummy variables, including agricultural district and year fixed effects.[a]

		(1)	(2)	(3)	(4)	(5)	(6)
Index		3-yr moving average		2-yr moving average		Own year indices	
Counties		All	Non-irrigated	All	Non-irrigated	All	Non-irrigated
Precipitation		0.245**	-0.006	0.234**	-0.013	0.215**	-0.033
		(1.038e-01)	(1.718e-01)	(9.540e-02)	(1.671e-01)	(9.268e-02)	(1.619e-01)
Joint Significance [b]		***	***	***	***	***	***
DD10		7.755***	10.159***	8.136***	10.529***	7.769***	11.019***
		(1.323)	(1.511)	(1.307)	(1.513)	(1.272)	(1.425)
$DD10^2$		-3.783***	-4.776***	-3.960***	-4.946***	-3.801***	-5.177***
		(6.345e-01)	(7.528e-01)	(6.264e-01)	(7.585e-01)	(6.084e-01)	(7.127e-01)
$DD10^3$		0.566***	0.695***	0.593***	0.720***	0.571***	0.755***
		(9.707e-02)	(1.174e-01)	(9.581e-02)	(1.192e-01)	(9.283e-02)	(1.120e-01)
Farm Pop (000)		0.389***	0.519***	0.391***	0.520***	0.392***	0.520***
		(4.798e-02)	(6.147e-02)	(4.680e-02)	(6.305e-02)	(4.660e-02)	(6.320e-02)
$D_C = 1$	γ_C	0.101	0.109	0.096	0.108	0.109	0.130*
		(7.059e-02)	(8.141e-02)	(6.639e-02)	(7.705e-02)	(6.640e-02)	(7.739e-02)
$D_A = 1$	γ_A	0.011	-0.030	0.005	-0.027	0.018	-0.001
		(9.240e-02)	(7.140e-02)	(8.440e-02)	(6.310e-02)	(8.480e-02)	(6.478e-02)
Crop Index	β_C	0.282	0.367	0.187	0.158	0.216	-0.187
		(3.110e-01)	(4.314e-01)	(2.849e-01)	(3.709e-01)	(2.612e-01)	(3.426e-01)
Animal Index	β_A	0.382	0.703	0.345	0.684	0.588**	0.952***
		(3.643e-01)	(5.346e-01)	(3.344e-01)	(4.847e-01)	(2.470e-01)	(3.578e-01)
Crop Idx $\times D_C = 1$	β_{CC}	-0.516*	-0.547*	-0.331	-0.299	-0.123	0.062
		(2.835e-01)	(3.227e-01)	(2.758e-01)	(3.183e-01)	(2.264e-01)	(2.716e-01)
Animal Idx $\times D_A = 1$	β_{AA}	-0.779**	-1.189**	-0.759***	-1.022**	-0.560***	-0.803**
		(3.643e-01)	(5.082e-01)	(2.749e-01)	(4.058e-01)	(2.158e-01)	(3.502e-01)
Crop Idx $\times D_A = 1$	β_{CA}	-0.165	-0.166	-0.077	-0.043	-0.054	0.017
		(2.875e-01)	(3.438e-01)	(2.715e-01)	(3.196e-01)	(2.229e-01)	(2.855e-01)
Animal Idx $\times D_C = 1$	β_{AC}	-0.449	-0.590	-0.492	-0.662	-0.552***	-0.947***
		(4.437e-01)	(6.269e-01)	(3.392e-01)	(5.173e-01)	(2.143e-01)	(3.494e-01)
Observations		50507	38573	53478	40842	56449	43111
Year F.E.		Y	Y	Y	Y	Y	Y
Joint Significance [c]		***	***	***	***	***	***
AIC		24961.32	18868.81	26526.06	20048.90	27964.75	21069.90
BIC		25217.39	19117.06	26792.67	20307.43	28241.92	21338.72
Crop: $(\beta_C + \beta_{CC})I_C$		-0.234	-0.18	-0.144	-0.141	0.093	-0.125
Crop: $(\beta_A + \beta_{AC})I_A$		-0.067	0.113	-0.147	0.022	0.036	0.005
Animal: $(\beta_C + \beta_{CA})I_C$		0.117	0.201	0.11	0.115	0.162	-0.17
Animal: $(\beta_A + \beta_{AA})I_A$		-0.397	-0.486	-0.414	-0.338	0.028	0.149

Note: Clustered standard errors by Agricultural district in parentheses.

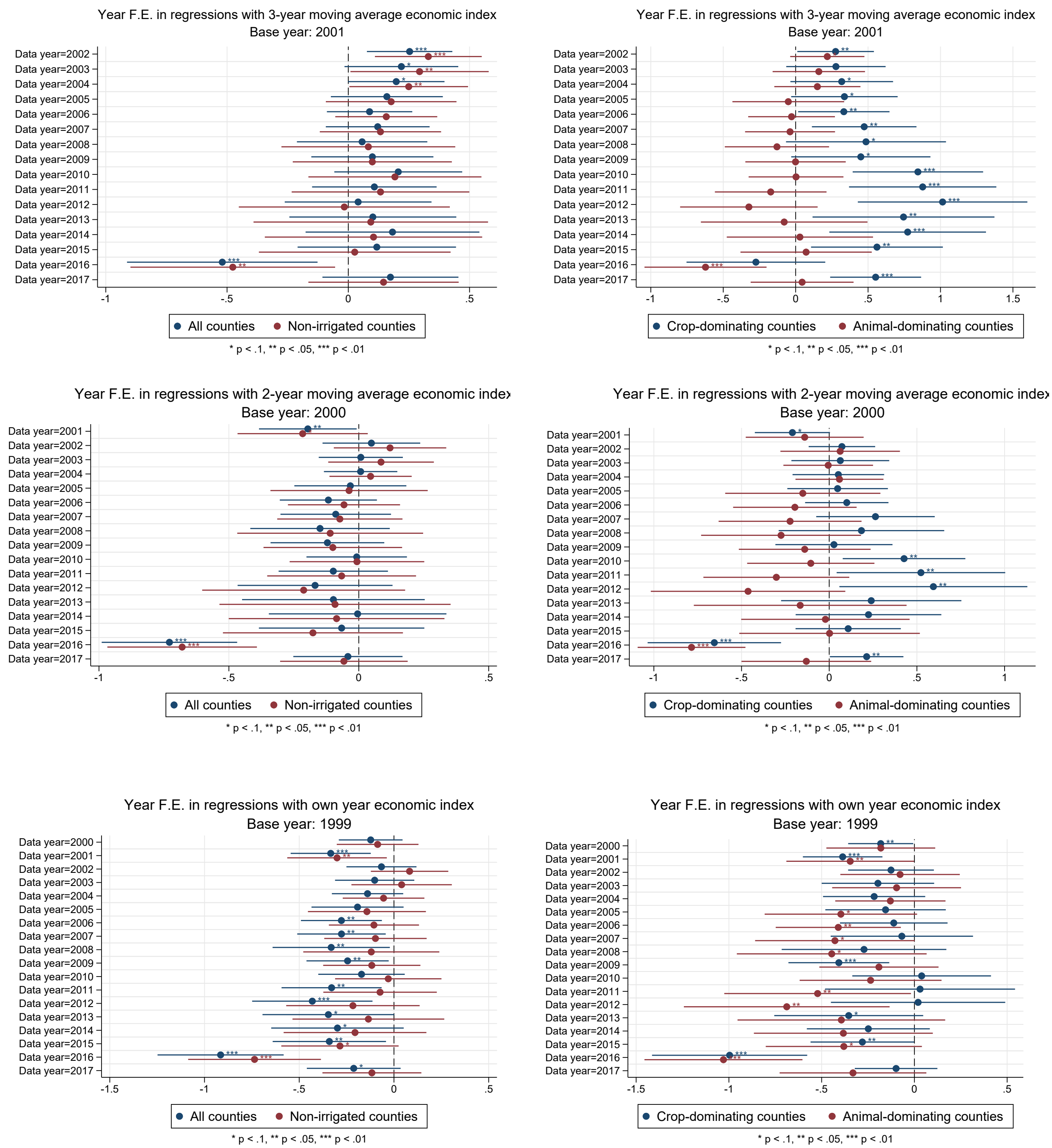
* $p < .1$, ** $p < .05$, *** $p < .01$

[a] Coefficients of year fixed effects are not displayed in this table.

[b] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.

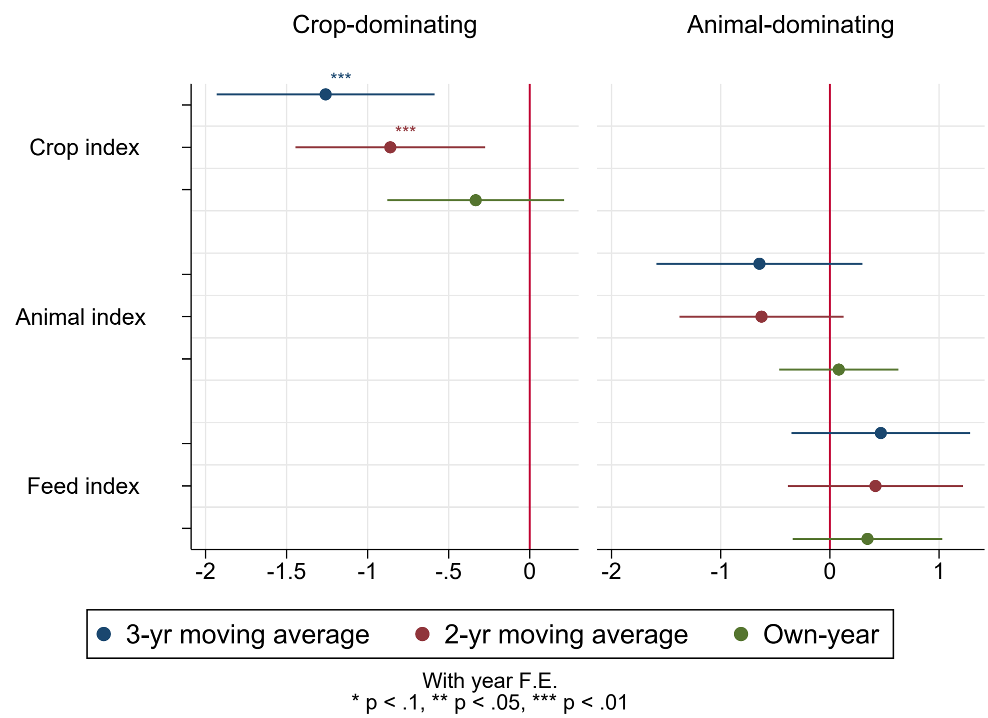
[c] The joint significance row indicates the joint significance of the year fixed effects.

Figure 32: Coefficients plot of year fixed effects in regression table 25 (L) and 26 (R)



Note: Horizontal lines represent 95 percent confidence intervals.

Figure 33: Coefficients plot of economic indexes in table 26 with year F.E.



Note: Horizontal lines represent 95 percent confidence intervals.

Table 26: Regression results: two sub-samples of crop- and animal-dominating counties, including agricultural district and year fixed effects.[a]

	(1)	(2)	(3)	(4)	(5)	(6)
Index	3-yr moving average		2-yr moving average		Own year indices	
Dominating	Crop	Animal	Crop	Animal	Crop	Animal
Precipitation	0.277**	0.313**	0.315**	0.284**	0.323**	0.256*
	(1.365e-01)	(1.283e-01)	(1.368e-01)	(1.313e-01)	(1.329e-01)	(1.388e-01)
Joint Significance[b]	***	***	***	***	***	***
DD10	9.525***	6.105***	10.249***	6.516***	10.917***	5.535***
	(2.436)	(1.453)	(2.453)	(1.395)	(2.268)	(1.337)
$DD10^2$	-4.291***	-3.116***	-4.672***	-3.314***	-5.022***	-2.871***
	(1.202)	(6.773e-01)	(1.203)	(6.539e-01)	(1.118)	(6.284e-01)
$DD10^3$	0.586***	0.483***	0.651***	0.514***	0.710***	0.451***
	(1.890e-01)	(1.018e-01)	(1.873e-01)	(9.966e-02)	(1.752e-01)	(9.558e-02)
Farm Pop (000)	0.520***	0.390***	0.524***	0.393***	0.517***	0.392***
	(8.206e-02)	(4.227e-02)	(8.454e-02)	(4.042e-02)	(9.041e-02)	(4.216e-02)
Crop Index	-1.259***		-0.860***		-0.333	
	(3.429e-01)		(2.986e-01)		(2.783e-01)	
Animal Index		-0.645		-0.626		0.082
		(4.814e-01)		(3.835e-01)		(2.786e-01)
Feed Index		0.466		0.417		0.344
		(4.175e-01)		(4.092e-01)		(3.495e-01)
Observations	19499	23205	20646	24570	21793	25935
Year F.E.	Y	Y	Y	Y	Y	Y
Joint Significance [c]	***	***	***	***	***	***
AIC	9701.21	11163.02	10336.84	11868.23	10927.94	12519.06
BIC	9874.53	11348.22	10519.35	12062.85	11119.68	12723.14

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] Coefficients of year fixed effects are not displayed in this table.
[b] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.
[c] The joint significance row indicates the joint significance of the year fixed effects.

Because crop and animal-product prices are determined in integrated national or international markets and tend to move together due to close economic relationships among the products, year fixed effects can capture much of the effect of periods of good and bad economic conditions for crop and animal farmers, causing the economic indexes themselves to lose some of their explanatory power.

Table 14 indicates the variation in farmer suicide is mostly temporal, which suggests many of the economic hardships experienced by farmers happen due to common factors like adverse national and international agricultural prices. Including year fixed effects picks up the common trends that result in less significant coefficients of indexes.

Comparison with non-farmer suicide

To further test the robustness of the results, we repeat the analysis using the same methods as in the previous section, treating non-farmer suicide count, instead of farmer suicide count, in a county in a year as the outcome variable, holding other elements of regressions unchanged. In order to make the comparison more systematic, counties classified as Metropolitan Statistical Areas (MSA), geographical regions with a relatively high population density in the U.S., are dropped from the non-farmer regressions. There are 1116 counties in our sample categorized as part of MSA. A summary statistics table of key variables by MSA status can be found in the Appendix.

The results are displayed in table 27 for the specification with interaction effects and in table 28 for the specification with two sub-samples. Agricultural district fixed effects are included in all regressions. Likewise, precipitation is in meters, and degree days are in thousand days for data-scaling purposes.

Following the same method, we use a third order polynomial to fit non-farmer suicide count to degree days above 10 °C. The three coefficients of degree days above 10°C are mainly not significant. The margin plots of non-farmer suicide count responding to increasing degree

Table 27: Non-farmer suicide regression results: interaction effects of economic indexes and dominating dummy variables including agricultural district fixed effects.[a]

		(1)	(2)	(3)	(4)	(5)	(6)
Index		3-yr moving average		2-yr moving average		Own year indices	
Counties		All	Non-irrigated	All	Non-irrigated	All	Non-irrigated
Precipitation		0.239**	0.412***	0.264***	0.443***	0.254**	0.422***
		(1.007e-01)	(7.911e-02)	(1.015e-01)	(8.066e-02)	(1.018e-01)	(7.982e-02)
Joint Significance[b]		***	***	***	***	***	***
DD10		-3.006**	-1.613	-3.072**	-1.676	-2.969**	-1.525
		(1.276)	(1.429)	(1.275)	(1.428)	(1.259)	(1.422)
$DD10^2$		1.263*	0.505	1.293*	0.534	1.247*	0.467
		(6.749e-01)	(7.451e-01)	(6.739e-01)	(7.437e-01)	(6.676e-01)	(7.433e-01)
$DD10^3$		-0.170	-0.042	-0.175	-0.046	-0.168	-0.036
		(1.147e-01)	(1.242e-01)	(1.144e-01)	(1.239e-01)	(1.136e-01)	(1.242e-01)
Farm Pop (000)		0.439***	0.445***	0.440***	0.447***	0.438***	0.444***
		(5.386e-02)	(2.923e-02)	(5.435e-02)	(2.919e-02)	(5.387e-02)	(2.865e-02)
$D_C = 1$	γ_C	-0.180***	-0.156*	-0.180***	-0.158*	-0.181***	-0.161*
		(6.540e-02)	(8.409e-02)	(6.526e-02)	(8.413e-02)	(6.486e-02)	(8.402e-02)
$D_A = 1$	γ_A	0.001	-0.002	0.000	-0.004	0.001	-0.004
		(7.424e-02)	(8.722e-02)	(7.419e-02)	(8.700e-02)	(7.386e-02)	(8.721e-02)
Crop Index	β_C	0.199***	0.217***	0.223***	0.216***	0.190***	0.166***
		(4.709e-02)	(5.903e-02)	(4.078e-02)	(4.750e-02)	(3.455e-02)	(4.188e-02)
Animal Index	β_A	0.514***	0.413***	0.386***	0.323***	0.276***	0.242***
		(4.748e-02)	(7.104e-02)	(4.155e-02)	(5.852e-02)	(4.081e-02)	(5.214e-02)
Crop Idx $\times D_C = 1$	β_{CC}	-0.011	-0.036	-0.047	-0.048	-0.061	-0.050
		(5.237e-02)	(6.412e-02)	(4.535e-02)	(5.411e-02)	(4.143e-02)	(4.944e-02)
Animal Idx $\times D_A = 1$	β_{AA}	-0.228***	0.028	-0.170**	-0.005	-0.091	0.007
		(6.831e-02)	(8.025e-02)	(6.620e-02)	(7.150e-02)	(6.783e-02)	(6.822e-02)
Crop Idx $\times D_A = 1$	β_{CA}	0.101	0.074	0.044	0.044	0.001	0.029
		(6.457e-02)	(6.291e-02)	(5.852e-02)	(5.684e-02)	(4.965e-02)	(4.846e-02)
Animal Idx $\times D_C = 1$	β_{AC}	-0.045	0.009	0.027	0.062	0.058	0.068
		(5.904e-02)	(7.639e-02)	(5.201e-02)	(6.458e-02)	(4.788e-02)	(5.778e-02)
Observations		31926	23494	33804	24876	35682	26258
AIC		167703.52	120290.09	176627.89	126724.64	185692.70	133283.48
BIC		167812.34	120394.93	176737.46	126830.22	185802.97	133389.77
Crop: $(\beta_C + \beta_{CC})I_C$		0.188	0.181	0.176	0.168	0.129	0.116
Crop: $(\beta_A + \beta_{AC})I_A$		0.469	0.422	0.413	0.385	0.334	0.31
Animal: $(\beta_C + \beta_{CA})I_C$		0.3	0.291	0.267	0.26	0.191	0.195
Animal: $(\beta_A + \beta_{AA})I_A$		0.286	0.441	0.216	0.318	0.185	0.249

Note: Clustered standard errors by agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] Regressions in this table do not include observations of counties located in Metropolitan Statistical Areas (MSA).

[b] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.

Table 28: Non-farmer suicide regression results: two sub-samples of crop- and animal-dominating counties including agricultural district fixed effects. [a]

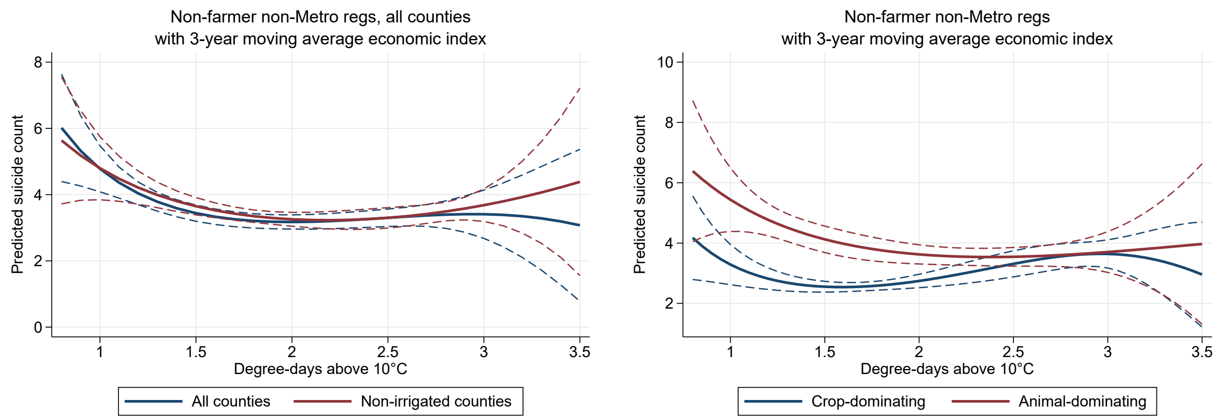
	(1)	(2)	(3)	(4)	(5)	(6)
Index	3-yr moving average		2-yr moving average		Own year indices	
Dominating	Crop	Animal	Crop	Animal	Crop	Animal
Precipitation	0.354**	0.132	0.378***	0.148	0.344**	0.150
	(1.431e-01)	(1.056e-01)	(1.447e-01)	(1.059e-01)	(1.452e-01)	(1.066e-01)
Joint Significance[b]	***	***	***	***	***	***
DD10	-3.945***	-1.642	-3.998***	-1.704	-3.891***	-1.671
	(1.344)	(1.646)	(1.338)	(1.657)	(1.334)	(1.625)
$DD10^2$	1.906***	0.539	1.923***	0.571	1.869***	0.559
	(7.100e-01)	(8.299e-01)	(7.056e-01)	(8.344e-01)	(7.062e-01)	(8.215e-01)
$DD10^3$	-0.279**	-0.054	-0.281**	-0.060	-0.272**	-0.058
	(1.189e-01)	(1.335e-01)	(1.182e-01)	(1.341e-01)	(1.187e-01)	(1.325e-01)
Farm Pop (000)	0.757***	0.357***	0.757***	0.359***	0.747***	0.358***
	(7.601e-02)	(5.255e-02)	(7.815e-02)	(5.310e-02)	(7.295e-02)	(5.268e-02)
Crop Index	0.277***		0.225***		0.112***	
	(3.131e-02)		(2.711e-02)		(2.496e-02)	
Animal Index		0.327***		0.249***		0.206***
		(5.344e-02)		(4.397e-02)		(4.083e-02)
Feed Index		0.301***		0.267***		0.203***
		(3.273e-02)		(2.954e-02)		(3.019e-02)
Observations	11781	15300	12474	16200	13167	17100
AIC	54496.66	81230.77	57414.78	85650.17	60476.62	90063.32
BIC	54540.90	81284.22	57459.36	85704.02	60521.54	90117.55

Note: Clustered standard errors by Agricultural district in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

[a] Regressions in this table do not include observations of counties located in Metropolitan Statistical Areas (MSA).
[b] The joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.

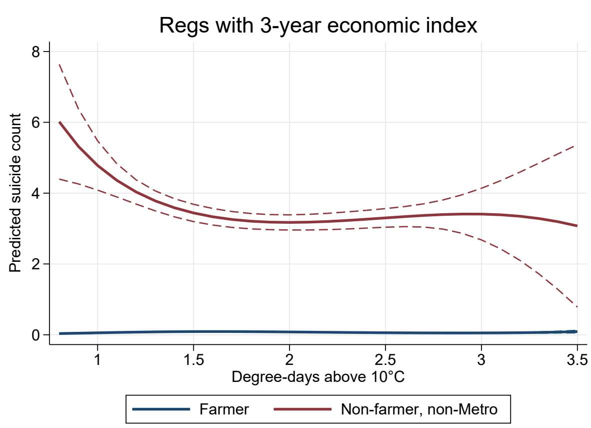
days above 10°C are presented in figure 34. Although the curve follows a cubic shape, the curvature of predicted non-farmer suicide in both plots is insignificant. The confidence interval band is wide at high degree days values for all the margin plot curves. The portion in the middle with a narrow confidence inverted band is mainly flat. The curvature is likely due to the curve fitting the cubic shape, despite the joint statistical significance found in the three cubic terms of degree days. Thus, the impact of cumulative heat on non-farmer suicide is negligible in most of the data range.[23]

Figure 34: Non-farmer expected suicide count and degree days above 10°C

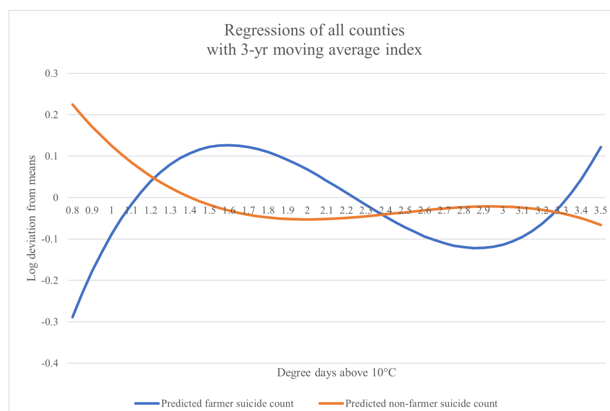


Note: Dashed lines indicate the 95% confidence interval bands.

Figure 35: Farmer and non-farmer expected suicide count and degree days above 10°C, a comparison of results in Table 27



(a) Direct comparison



(b) Log deviation comparison

Note: Dashed lines in plot (a) indicate the 95% confidence interval bands. Confidence bands are not shown in the log deviation figures.

Figures 35 and 36 compare predicted farmer and non-farmer suicide count as a cubic function of degree days above 10 °C. Due to the large disparity in magnitude of predicted

[23]Note that this set of regressions is not designed to estimate the non-farmer suicide count. The results shown here are used as references to provide robust evidence to our results in farmer suicide regressions.

farmer suicide count and non-farmer suicide count, the margin plot of farmer suicide count is distorted as a flat line in the sub-figure (a) in figure 35. Plotting the two curves in the same figure does not deliver an effective comparison. Thus, we compute a log deviation of the predicted suicide count from the mean values as the sub-figure on the right in figure 35 to show a relative change in suicide count as degree days increase, as follows:

$$LD_{DD} = \log(y_{DD}) - \log(y_{\bar{DD}}),$$

where $DD = 0.8, ..., 3.5$. y_{DD} denotes the predicted suicide count given degree days above 10°C holding all other variables at constant. $y_{\bar{DD}}$ is the mean value of all the predicted suicide counts over the degree days range. The blue and orange curves in sub-figure (b) in figure 35 represent the log deviation of predicted farmer suicide count and predicted non-farmer suicide count, respectively, given degree days ranging from 0.8 to 3.5.

Subplot (b) in figure 35 indicates that warm temperature or appropriate heat accumulation benefits farmers as it facilitates plant growth, but is not associated with non-farmer suicide. If we treat the effect of degree days on non-farmer suicides as a proxy for the psychological effect of degree days on farmer suicides, we can infer that the effect of degree days on farmer suicides through the farming channel is mostly beneficial, or negative.

Following the same method, the log deviation of the predicted suicide count is computed after the estimations of regressions of two sub-samples. Plots of log deviations from the crop- and animal-dominating counties regressions are demonstrated in figure 36.

In the crop-dominating counties, more heat accumulation benefits farmers as the curve decreases at most of the degree days levels. Since heat does not significantly impact non-farmers, increasing temperature reduces farmer suicide through the farming channel, as crop farmers can rely on technologies such as irrigation to deal with extreme heat and dry conditions. Although there are technologies to reduce heat stress to farm animals, it is generally harder to adapt to extreme heat in animal agriculture than in crop agriculture.

Figure 37 shows a comparison of coefficients of economic indexes in table 23 and table 28, in which the outcome variable is farmer suicide count and non-farmer suicide count, respectively, excluding year fixed effects. The economic indexes are not expected to be associated with non-farmer suicide unless they could possibly reflect an adverse effect due to food prices. The three-year and two-year moving average crop, animal and feed economic index are associated with positive effects on non-farmer suicide. Importantly effects of the indexes on non-farmer suicide are opposite to the effects on farmers.

However, if the economic indexes can represent food prices, they are likely to be correlated with time-varying error terms as the variation in food prices are mainly temporal. Excluding year fixed effects might cause omitted variable bias. Thus, it is worth presenting the coefficients of economic indexes from regressions including year fixed effects. Comparing

Figure 36: Farmer and non-farmer expected suicide count and degree days above 10°C, a log deviation comparison of results in table 28

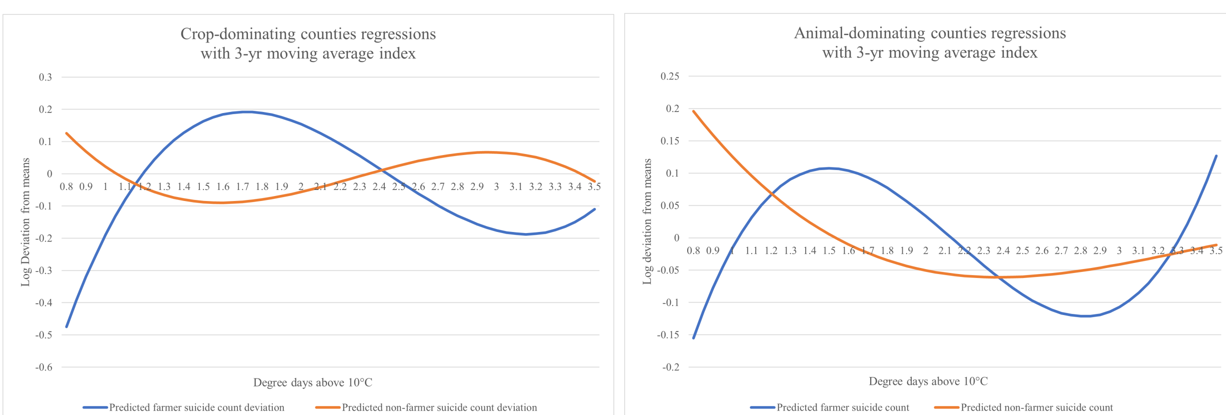
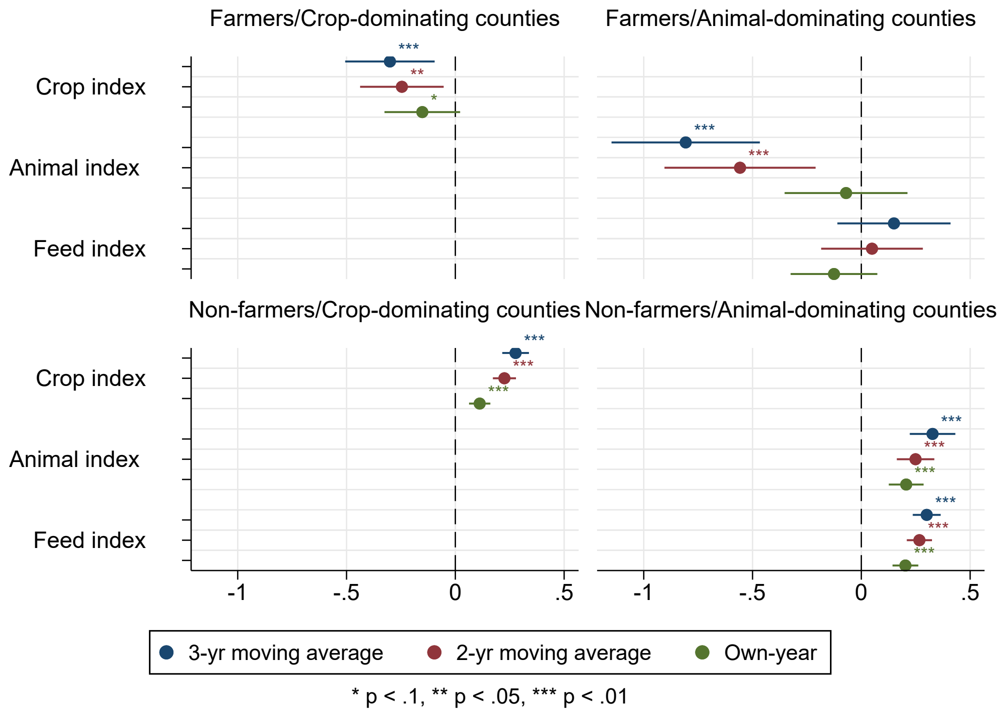


Figure 37: Coefficients plot of economic indexes: a comparison between farmer and non-farmer suicide regressions in table 23 and 28

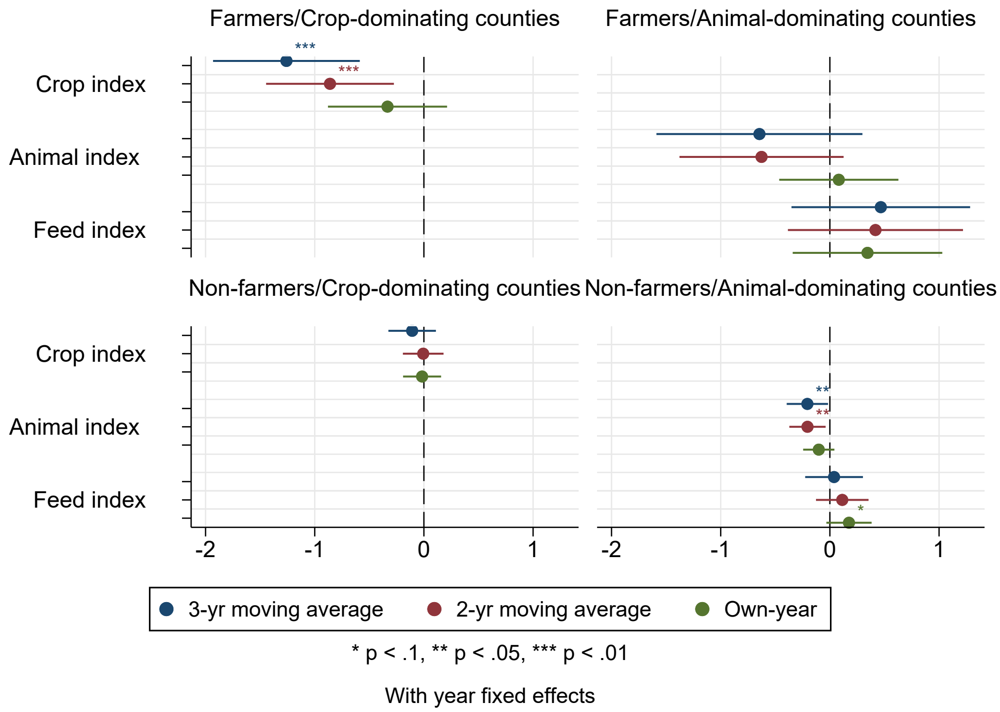


Note: Horizontal lines represent 95 percent confidence intervals.

figure 38 and figure 37, the negative effect of the crop economic index on farmer suicide in crop-dominating counties is robust. There are no cross-sectional effects of crop index on non-farmers in crop-dominating non-Metro counties.

The comparison of farmer and non-farmer suicide regressions provide robust evidence to our findings that the effect of precipitation on farmer suicide depends on the baseline precipitation level. Given the psychological effect of precipitation are likely to be positive, the effect of precipitation through the farming channel in non-irrigated counties might be negative, and in irrigated counties might be positive. Degree days are negatively associated with farmer suicides at low to medium levels. High heat might be positively associated

Figure 38: Coefficients plot of economic indexes: a comparison between farmer and non-farmer suicide regressions including year fixed effects



Note: Horizontal lines represent 95 percent confidence intervals.

with farmer suicides, especially for farmers involved in animal agriculture. Chronic poor agricultural economic conditions are positively associated with farmer suicides.

5 Conclusion

Farmers commit suicide at a higher rate than most of the rest of the population, and the rate is elevating in the U.S. and elsewhere. Better understanding of the determinants of farmer suicide and improving the effectiveness of suicide prevention is increasingly important. However, the factors behind farmer suicide have lacked rigorous study. This study has sought to address this void by exploring the effects of the weather and economic factors (extreme temperatures, variable precipitation, and variable agricultural prices) on farmer suicide in the U.S.

This study developed a theoretical model linking the weather and economic factors to a farmer's suicide decision under the framework of constrained utility maximization. Farmers have to balance work and leisure, consumption, production input investment, and saving, given uncertainties inherent in their occupation. Adverse weather conditions and unfavorable prolonged economic conditions can deepen farmers' perception of a discouraging future. They are more likely to see themselves experiencing poor income, limited savings, and/or poor life quality. This "snowballing" effect may induce farmers to take on additional workload to minimize the damage to business caused by bad weather and/or poor economic conditions, thus worsening quality of life and jeopardizing health.

Thus, adverse weather outcomes and/or poor economic conditions, particularly those that are chronic, possibly diminish a farmer's hope and trigger the suicide decision in extreme cases. The theoretical model yields hypotheses that the marginal effect of harmful weather and bad economic conditions on farmer suicide is positive.

This study utilizes data retrieved from the CDC nonpublic vital statistics, PRISM daily weather data, and the USDA NASS Census of Agriculture and constructs a county-year panel in the U.S, spanning 19 years from 1999 to 2017. Assuming farmer suicide count in a county in a year follows the Poisson distribution, we estimate the marginal effects of weather and economic factors based upon a Poisson regression model with agricultural district fixed effects.

We find no clear evidence of the effect of precipitation on farmer suicide in counties without irrigation and a positive effect of precipitation on farmer suicide in general through physical and mental health, or both. By analyzing the non-farmer suicide regressions as a proxy for the psychological effect of precipitation on farmer suicides, we can infer that the precipitation effect through the farming channel is heterogeneous based upon the baseline precipitation level. More precipitation might increase farmer suicides in irrigated counties and may reduce farmer suicides in non-irrigated counties.

We find a negative association between warm temperature and farmer suicides and a weak association between cumulative heat and farmer suicide. As we fit the expected farmer suicide as a cubic function of degree days, the low and medium values of degree days portion of the curve is decreasing. An increasing portion shows at high degree day values. However, the 95% confidence interval expands widely as degree days increase, indicating an imprecise estimation. The effect of extreme temperatures is more definitive in counties where animal production is dominant than in crop-dominating counties.

Empirical results suggest that a single year of low agricultural prices is not associated with farmer suicide. Rather, prolonged periods of bad economic conditions may motivate suicide. For example, a 10% increase in the three-year moving average real crop prices reduces the expected farmer suicide count by about 2.29%-3.01% in crop-dominating counties. In animal-dominating counties, a 10% price increase in the three-year moving average real animal prices is associated with a 7.91%-8.07% decrease in the expected farmer suicide count.

The findings in the empirical analysis are consistent with the hypothesis derived from the theoretical model: beneficial weather conditions reduce farmer suicides. Bad weather is one of several factors that may cause poor farm income, which when endured for successive years, may cause suicide. Consecutive bad years for farm income caused by chronic, not idiosyncratic, poor economic conditions appear to be a significant causal factor in farmer suicide.

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Appendix

Table 29: Baseline regressions: linear and quadratic precipitation with degree days above 8°C

	(1)	(2)	(3)	(4)	(5)	(6)
Joint Significance[a]				***	**	**
Optimal(mm)				997	1071	1014
Precipitation	0.257***	0.212**	0.206**	0.785**	0.544	0.576*
	(8.805e-02)	(8.441e-02)	(8.235e-02)	(3.642e-01)	(3.593e-01)	(3.308e-01)
Precipitation^2				-0.406	-0.254	-0.284
				(2.569e-01)	(2.580e-01)	(2.383e-01)
Joint Significance[b]		**	***		**	***
Optimal(days)		1953	1919,3257		1925	1914,3245
DD8	-0.177***	0.742*	8.907***	-0.175***	0.693*	8.887***
	(5.737e-02)	(3.821e-01)	(1.410)	(5.705e-02)	(3.908e-01)	(1.431)
DD8^2		-0.190**	-3.688***		-0.180**	-3.691***
		(8.493e-02)	(5.802e-01)		(8.600e-02)	(5.867e-01)
DD8^3			0.475***			0.477***
			(7.678e-02)			(7.749e-02)
Farm Pop(000)	0.391***	0.392***	0.375***	0.393***	0.393***	0.376***
	(4.439e-02)	(4.624e-02)	(4.289e-02)	(4.460e-02)	(4.622e-02)	(4.286e-02)
Observations	56639					
Ag district F.E.	Y	Y	Y	Y	Y	Y
AIC	28179.40	28160.80	28084.29	28176.68	28161.02	28084.05
BIC	28206.24	28196.58	28129.01	28212.46	28205.74	28137.72

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] The Joint significance row indicates the joint significance of three coefficients of the linear and quadratic terms of precipitation.

[b] The Joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 8°C.

Table 30: Baseline regressions: linear and quadratic precipitation with GDD between 8°C to 32°C and HDD above 32°C

	(1)	(2)	(3)	(4)	(5)	(6)
Joint Significance[a]				***	**	**
Optimal(mm)				1023	1304	1151
Precipitation	0.312***	0.316***	0.285***	0.878**	0.639*	0.665*
	(1.090e-01)	(1.097e-01)	(1.032e-01)	(3.616e-01)	(3.658e-01)	(3.429e-01)
Precipitation^2				-0.429*	-0.245	-0.289
				(2.545e-01)	(2.586e-01)	(2.406e-01)
Joint Significance[b]		***	***		***	***
Optimal(days)		1898	1891,3303		1874	1882,3276
GDD8-32	-0.215***	0.972**	8.883***	-0.219***	0.922**	8.878***
	(7.471e-02)	(3.844e-01)	(1.529)	(7.554e-02)	(3.940e-01)	(1.548)
GDD8-32^2		-0.256***	-3.693***		-0.246***	-3.705***
		(8.471e-02)	(6.375e-01)		(8.597e-02)	(6.437e-01)
GDD8-32^3			0.474***			0.477***
			(8.492e-02)			(8.558e-02)
HDD32	0.093	0.198	0.191	0.110	0.205	0.199
	(2.256e-01)	(2.196e-01)	(2.139e-01)	(2.257e-01)	(2.195e-01)	(2.136e-01)
Farm Pop(000)	0.391***	0.392***	0.376***	0.393***	0.393***	0.377***
	(4.384e-02)	(4.574e-02)	(4.239e-02)	(4.391e-02)	(4.566e-02)	(4.229e-02)
Observations	56639					
Ag district F.E.	Y	Y	Y	Y	Y	Y
AIC	28179.79	28150.06	28089.95	28176.57	28150.40	28089.64
BIC	28215.57	28194.78	28143.61	28221.29	28204.07	28152.25

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] The Joint significance row indicates the joint significance of three coefficients of the linear and quadratic terms of precipitation.

[b] The Joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of growing degree days between 8°C and 32°C.

Table 31: Summary statistics of key variables by irrigation status, full sample

Sub-sample	Non-irrigated counties	Irrigated counties	Non-metro areas	Metro areas
Observations	43966	13737	36309	21394
Farmer suicide count	0.07	0.08	0.05	0.10
Non-farmer suicide count	10.05	15.80	3.40	25.03
Precipitation (mm)	723.33	364.62	614.69	677.37
Degree days above 8°C	2443.55	2211.94	2329.07	2489.12
Degree days above 10°C	2081.42	1874.69	1978.45	2123.43
Growing degree days 8°C - 32°C	2427.63	2175.85	2308.14	2468.76
Growing degree days 10°C - 34°C	2076.57	1858.82	1970.93	2116.05
Degree days above 32°C	15.92	36.09	20.94	20.36
Degree days above 34°C	4.85	15.87	7.53	7.37
Farm Population	990.88	1230.23	928.77	1253.56
Economic variables (in 2017$)				
Crop sales	4.05e+07	8.28e+07		
Cattle sales	1.29e+07	5.26e+07		
Hogs sales	7.80e+06	2.39e+06		
Dairy sales	8.23e+06	2.07e+07		
Poultry sales	1.50e+07	4.41e+06		

Table 32: Regression results of irrigated counties: interaction effects of economic indexes and dominating dummy variables including agricultural district and year fixed effects[a]

		(1)	(2)	(3)	(4)	(5)	(6)
Index		3-yr moving average		2-yr moving average		Own year indices	
Precipitation		-0.072	-0.093	-0.158	-0.145	-0.197	-0.185
		(2.094e-01)	(2.117e-01)	(2.073e-01)	(2.118e-01)	(1.783e-01)	(1.870e-01)
Joint Significance [b]							
DD10		1.523	1.727	1.716	1.961	0.820	1.182
		(2.062)	(2.046)	(2.007)	(1.969)	(1.705)	(1.660)
$DD10^2$		-0.871	-0.988	-0.954	-1.085	-0.561	-0.721
		(1.057)	(1.049)	(1.020)	(9.977e-01)	(8.722e-01)	(8.486e-01)
$DD10^3$		0.159	0.180	0.172	0.194	0.118	0.141
		(1.713e-01)	(1.695e-01)	(1.640e-01)	(1.600e-01)	(1.414e-01)	(1.376e-01)
Farm Pop(000)		0.276***	0.276***	0.275***	0.277***	0.269***	0.281***
		(5.304e-02)	(5.307e-02)	(5.020e-02)	(5.037e-02)	(4.752e-02)	(4.931e-02)
$D_C = 1$	γ_C	0.002	0.003	-0.016	-0.013	-0.018	-0.015
		(1.620e-01)	(1.611e-01)	(1.555e-01)	(1.550e-01)	(1.471e-01)	(1.477e-01)
$D_A = 1$	γ_A	0.145	0.146	0.115	0.117	0.126	0.122
		(1.858e-01)	(1.853e-01)	(1.708e-01)	(1.709e-01)	(1.667e-01)	(1.692e-01)
Crop Index	β_C	0.201	-0.000	0.146	0.107	0.160	0.642
		(3.420e-01)	(4.659e-01)	(2.902e-01)	(4.003e-01)	(3.175e-01)	(4.136e-01)
Animal Index	β_A	-0.311	-0.551	-0.082	-0.498	-0.037	-0.111
		(5.266e-01)	(8.544e-01)	(4.904e-01)	(7.829e-01)	(4.706e-01)	(6.358e-01)
Crop Idx $\times D_C = 1$	β_{CC}	0.126	0.185	-0.035	-0.025	-0.285	-0.359
		(3.537e-01)	(3.676e-01)	(3.063e-01)	(3.318e-01)	(3.351e-01)	(3.464e-01)
Animal Idx $\times D_A = 1$	β_{AA}	-0.057	-0.050	-0.206	-0.197	0.096	0.037
		(6.544e-01)	(6.471e-01)	(6.123e-01)	(5.721e-01)	(5.535e-01)	(5.168e-01)
Crop Idx $\times D_A = 1$	β_{CA}	0.087	0.075	-0.063	-0.054	-0.263	-0.194
		(3.850e-01)	(4.006e-01)	(3.856e-01)	(4.118e-01)	(4.210e-01)	(4.185e-01)
Animal Idx $\times D_C = 1$	β_{AC}	-0.353	-0.364	-0.244	-0.182	0.256	0.311
		(5.948e-01)	(5.836e-01)	(5.243e-01)	(4.843e-01)	(5.095e-01)	(4.750e-01)
Observations		11832	11832	12582	12582	13281	13281
Ag district F.E.		Y	Y	Y	Y	Y	Y
Year F.E.		N	Y	N	Y	N	Y
Joint significance [c]			***		***		***
AIC		5850.48	5848.30	6231.23	6227.12	6629.48	6617.70
BIC		5946.40	6062.28	6327.95	6450.32	6726.90	6850.02
Crop: $(\beta_C + \beta_{CC})I_C$		0.327	0.185	0.111	0.082	-0.125	0.283
Crop: $(\beta_A + \beta_{AC})I_A$		-0.664	-0.915	-0.326	-0.68	0.219	0.2
Animal: $(\beta_C + \beta_{CA})I_C$		0.288	0.075	0.083	0.053	-0.103	0.448
Animal: $(\beta_A + \beta_{AA})I_A$		-0.368	-0.601	-0.288	-0.695	0.059	-0.074

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] Coefficients of year fixed effects are not displayed in this table.

[b] The Joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C. Note that none of the three coefficients are jointly significant in all regressions.

[c] The Joint significance row indicates the joint significance of the year fixed effects in regression (2), (4), and (6).

Table 33: Regression results: growing degree days and harmful degree days with interaction effects of economic indexes and dominating dummy variables including agricultural district and year fixed effects[a]

Index		(1) 3-yr moving average	(2)	(3) 2-yr moving average	(4)	(5) Own year indices	(6)
Precipitation (m)		0.378***	0.378***	0.373***	0.371***	0.351***	0.352***
		(9.363e-02)	(1.005e-01)	(8.577e-02)	(9.027e-02)	(8.584e-02)	(8.972e-02)
Joint Significance [b]		***	***	***	***	***	***
Extreme point (days)		1520	1529	1545	1564	1500	1523
GDD10-34		0.754**	0.743**	0.788**	0.785**	0.729**	0.728**
		(3.643e-01)	(3.716e-01)	(3.691e-01)	(3.759e-01)	(3.633e-01)	(3.706e-01)
GDD10-34^2		-0.248***	-0.243***	-0.255***	-0.251***	-0.243***	-0.239**
		(9.102e-02)	(9.246e-02)	(9.296e-02)	(9.408e-02)	(9.381e-02)	(9.486e-02)
HDD34		0.540*	0.592**	0.591**	0.601**	0.629**	0.608**
		(2.762e-01)	(2.585e-01)	(2.676e-01)	(2.612e-01)	(2.736e-01)	(2.807e-01)
Farm Pop(000)		0.408***	0.410***	0.410***	0.413***	0.404***	0.413***
		(4.981e-02)	(5.035e-02)	(4.861e-02)	(4.937e-02)	(4.732e-02)	(4.921e-02)
$D_C = 1$	γ_C	0.121*	0.122*	0.116*	0.118*	0.128*	0.130**
		(7.002e-02)	(6.951e-02)	(6.580e-02)	(6.538e-02)	(6.595e-02)	(6.564e-02)
$D_A = 1$	γ_A	-0.007	-0.010	-0.016	-0.019	0.001	-0.004
		(9.423e-02)	(9.464e-02)	(8.610e-02)	(8.662e-02)	(8.579e-02)	(8.655e-02)
Crop Index	β_C	0.277	0.177	0.114	0.127	-0.065	0.160
		(2.553e-01)	(3.144e-01)	(2.480e-01)	(2.856e-01)	(2.079e-01)	(2.656e-01)
Animal Index	β_A	0.062	0.416	0.225	0.347	0.465***	0.623***
		(3.256e-01)	(3.523e-01)	(2.438e-01)	(3.242e-01)	(1.718e-01)	(2.402e-01)
Crop Idx $\times D_C = 1$	β_{CC}	-0.549*	-0.516*	-0.351	-0.346	-0.095	-0.140
		(2.831e-01)	(2.862e-01)	(2.759e-01)	(2.793e-01)	(2.239e-01)	(2.293e-01)
Animal Idx $\times D_A = 1$	β_{AA}	-0.782**	-0.755**	-0.737***	-0.745***	-0.518**	-0.544***
		(3.456e-01)	(3.618e-01)	(2.752e-01)	(2.698e-01)	(2.212e-01)	(2.089e-01)
Crop Idx $\times D_A = 1$	β_{CA}	-0.189	-0.177	-0.103	-0.084	-0.086	-0.057
		(2.877e-01)	(2.917e-01)	(2.711e-01)	(2.758e-01)	(2.245e-01)	(2.253e-01)
Animal Idx $\times D_C = 1$	β_{AC}	-0.431	-0.438	-0.499	-0.477	-0.613***	-0.548**
		(4.324e-01)	(4.433e-01)	(3.484e-01)	(3.397e-01)	(2.212e-01)	(2.126e-01)
Observations		50507	50507	53478	53478	56449	56449
Ag district F.E.		Y	Y	Y	Y	Y	Y
Year F.E.		N	Y	N	Y	N	Y
Joint significance [c]			***		***		***
AIC		25044.29	25010.47	26622.46	26583.79	28070.81	28020.02
BIC		25159.08	25266.53	26737.99	26850.40	28187.05	28297.19
Crop: $(\beta_C + \beta_{CC})I_C$		-0.272*	-0.339*	-0.237	-0.219	-0.16	0.02
Crop: $(\beta_A + \beta_{AC})I_A$		-0.369	-0.022	-0.274	-0.13	-0.148***	0.075***
Animal: $(\beta_C + \beta_{CA})I_C$		0.088	0	0.011	0.043	-0.151	0.103
Animal: $(\beta_A + \beta_{AA})I_A$		-0.72**	-0.339**	-0.512***	-0.398***	-0.053***	0.079***

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] Coefficients of year fixed effects are not displayed in this table.
[b] The Joint significance row indicates the joint significance of two coefficients of the linear and quadratic terms of growing degree days 10°C-34°C.
[c] The Joint significance row indicates the joint significance of the year fixed effects in regression (2), (4), and (6).

Table 34: Regression results: two sub-samples of crop- and animal-dominating counties including agricultural district fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Index	3-yr moving average		2-yr moving average		Own year indices	
Dominating	Crop	Animal	Crop	Animal	Crop	Animal
Precipitation (m)	0.144	0.482***	0.197	0.462***	0.178	0.450***
	(1.517e-01)	(1.259e-01)	(1.519e-01)	(1.207e-01)	(1.569e-01)	(1.194e-01)
Joint Significance[a]	***	***	***	***	***	***
Extreme point (days) [b]	1886	(−)	1885	45 (−)	1890	(−)
GDD10-34	2.841***	-0.018	2.797***	0.006	2.854***	-0.125
	(6.251e-01)	(3.625e-01)	(6.348e-01)	(3.553e-01)	(6.062e-01)	(3.292e-01)
GDD10-34^2	-0.753***	-0.062	-0.742***	-0.067	-0.755***	-0.041
	(1.744e-01)	(8.844e-02)	(1.764e-01)	(8.785e-02)	(1.706e-01)	(8.523e-02)
HDD34	-0.770	0.567	-0.552	0.654*	-0.540	0.705**
	(6.057e-01)	(3.488e-01)	(5.679e-01)	(3.415e-01)	(5.815e-01)	(3.375e-01)
Farm Pop(000)	0.526***	0.413***	0.528***	0.416***	0.505***	0.408***
	(7.937e-02)	(4.247e-02)	(8.215e-02)	(4.014e-02)	(8.526e-02)	(3.987e-02)
Crop Index	-0.283***		-0.235**		-0.144*	
	(1.037e-01)		(9.568e-02)		(8.727e-02)	
Animal Index		-0.728***		-0.496***		-0.018
		(1.961e-01)		(1.915e-01)		(1.519e-01)
Feed Index		0.114		0.019		-0.170
		(1.423e-01)		(1.288e-01)		(1.145e-01)
Observations	19499	23205	20646	24570	21793	25935
AIC	9730.75	11186.63	10369.05	11898.50	10967.22	12548.63
BIC	9778.02	11243.00	10416.66	11955.26	11015.16	12605.77

Note: Clustered standard errors by Agricultural district in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

[a] The Joint significance row indicates the joint significance of three coefficients of the linear, quadratic, and cubic terms of degree days above 10°C.

[b] (−) denotes the value of extreme point is negative. The quadratic curve on the positive GDD range is strictly decreasing.