POWDERY MILDEW RISK & FORECASTING IN WINE GRAPES: DO GROWERS CHANGE RISK MANAGEMENT STRATEGIES IN RESPONSE TO DISEASE FORECASTS?

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ABSTRACT

How and how well growers manage the risks inherent in agriculture has direct welfare implications for producers and consumers at both local and societal levels. While better weather, pest and disease forecast information are rapidly disseminating among producers and are often touted as promising inputs to production and risk management, little is known about how this new information actually shapes producer behavior in practice. We argue that better forecast information can benefit growers and improve their capacity to manage disease and pests effectively, but that we must jointly consider the various margins of adjustment available to growers in order to properly understand their response to this improved information. Using the case of California wine grape growers and high resolution panel data that includes plot-level powdery mildew treatments, we characterize growers' response to a popular powdery mildew risk model that generates forecast in the form of a daily risk index (PMI). Our analysis suggests that growers using the PMI primarily adjust their choice of product in response to the PMI by switching to higher potency synthetic fungicides when the risk is high. Since these products have longer minimum intervals, this implies that – if anything – PMI users have longer intervals as the PMI increases. Our preliminary results also suggest that the net environmental impact of this documented multi-dimensional response to the PMI may actually be negative, although we emphasize that these are preliminary results. Futhermore, it is important to note that the magnitude of this effect is small compared to the general improvements in wine grape growers' environmental impact over the past several years.

JEL Codes : D8, Q1, Q5

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Powdery Mildew Risk & Forecasting in Wine grapes: Do Growers Change Risk Management Strategies in Response to Disease Forecasts?

How well or poorly agricultural producers manage the risks inherent in agriculture has direct welfare implications for producers and consumers at both local and societal levels. Furthermore, producers' behavioral responses to these risks can have environmental implications and other spillover effects. Generously over-spraying pesticides, for example, can provide insurance protection for a producer (Mumford and Norton, 1984) – a form of insurance that is effectively subsidized by external environmental and human health costs borne by society. Over-spraying pesticides is a particularly attractive form of insurance when crop insurance against pest damages is unavailable or relatively expensive (Carlson, 1979; Feinerman et al., 1992) or when pest outbreaks are unpredictable. Motivated by the latter justification for using pesticides as insurance, integrated pest management (IPM) aims to reduce pesticides by *inter alia* providing growers with better, more precise pest information – an objective that has been facilitated by rapid advances in remote sensing, telemetry, GPS, and other technologies that improve the collection and processing of high resolution spatial data. While better weather, pest and disease forecast information are often touted as promising inputs to production and risk management – inputs that enable producers to refine their expectations and operations – little is known about how this new information actually shapes producer behavior in practice.

The dynamics of agricultural production, risk management and pesticide use are distinctly crop- and location-specific. In the case of California wine grape growers, the management of powdery mildew risk is among the most important management practices. Growers' only real hope in the powdery mildew battle is proper preventative management, which is complicated by the explosive episodes of powdery mildew growth that are possible when optimal temperature and humidity conditions prevail. These growth explosions pose substantial production risks to growers; an entire season can be lost with a single poorly timed powdery mildew treatment. In response, growers apply heavy and frequent doses of sulfur products and relatively more toxic synthetic fungicides[1] in their vineyards, which are often located in picturesque but environmentally sensitive areas. The importance of vineyard location in the branding of wines can amplify growers' sensitivities to the environmental impacts of their production practices (Friedland, 2002; Warner, 2007) and their interest in local partnerships for promoting sustainable viticulture practices (Broome and Warner, 2008).

Founded on the observation that powdery mildew growth is largely a function of length of exposure to different temperature ranges, the Gubler-Thomas Powdery Mildew Index (PMI) (Thomas et al., 1994; Weber et al., 1996) is designed to help growers anticipate outbreaks so they can more precisely time their preventative powdery mildew treatments and reduce fungicide applications in the process. The social and environmental benefits of reduced fungicide use due to better treatment timing could be substantial. Grape growing countries worldwide stand to reap similar benefits from these disease forecasts. Yet, the purported value of the PMI to growers has been extrapolated from controlled field trials in which powdery mildew treatments are strictly determined by the PMI. Does the PMI change growers' management of powdery mildew risks in practice? If so, do these changes lead to a reduction in pesticide application? In addressing these questions, this paper is the most rigorous assessment to date of the value to agricultural producers of disease forecasting as a risk management tool. While we focus on California wine grape growers and the PMI in this paper, the availability of high resolution weather data has prompted the development of several similar forecast models. Our empirical analysis sheds a broader light on the value of forecasts derived from these models to producers and to society more broadly.

We estimate models of growers' disease management strategies using high resolution temporal and spatial data collected at the grower- and plot-level. We have collected and compiled this data from three sources: (i) a detailed survey of California grape growers that among other things elicited their perceptions and use of the PMI, (ii) Pesticide Use Reports (available from the California Department of Pesticide Regulation) that include detailed pesticide use histories for all California grape growers since 1990, and (iii) detailed intra-day weather data for dozens of weather stations throughout the grape growing regions of California since 1996.

[1] Synthetic fungicides fall mainly in the category of either sterol inhibitors or strobilurins.

The temporal and spatial resolution of this data allows us to estimate the value of disease forecasts at an unprecedented level of detail. We leverage the panel structure of our data to identify the actual impact of PMI use on pesticide applications.

Our results suggest that contrary to the intent of the PMI model, most growers do not adjust treatment intervals in response to this forecast information. Instead, the growers who use the PMI most heavily use it to decide *what* to spray rather than *when* to spray. This response, however, is mediated importantly by the value and susceptibility of the grapes produced. We use the panel nature of the data to explore the dynamics of this response over time. Finally, in order to estimate the impact of the PMI on total pesticide usage, we use established toxicity measures to evaluate the net environmental impact of growers' response to the PMI.

We begin by providing an overview of the economics of pesticide use, of agricultural forecast information, and of California wine grapes and our forecast of interest, the PMI. We formulate an economic model to convey the essential economic considerations in growers' response to disease forecast information in Section 2. We describe the data we use in detail in Section 3. In Section 4, we present and discuss our evaluation of how the PMI has changed growers' pest management strategies. After documenting these grower responses, we assess the net environmental impact attributable to these PMI responses. We conclude in Section 5.

1 Background

The Economics of Pesticide Use

There is a rich literature in economics focused on pesticide use. In this subsection, we quickly review a few strands in this literature that are directly relevant to our analysis. Broad reviews of the theoretical and empirical issues addressed in this literature are available elsewhere (see Carlson and Wetzstein, 1993; Fernandez-Cornejo et al., 1998; Norgaard, 1976). Much of this work, including research on insect-transmitted disease among California wine grapes (Brown et al., 2002), has modeled the economics of pest control with increasingly complex assumptions about pest populations and spatial relationships.

The relationship between pesticide use, production risk and risk aversion has figured prominently in this area of research. The conventional view is that many growers over use pesticides as a form of insurance (Mumford and Norton, 1984). Based on this view, crop insurance can in principle reduce the use of pesticides as insurance (Carlson, 1979; Feinerman et al., 1992). However, evidence from the U.S. Midwest suggests that crop insurance may increase pesticide use in practice (Horowitz and Lichtenberg, 1993). The theoretical work that suggests pesticides are risk-reducing hinges crucially on the assumption that pest damage is independent of other factors that affect output (Horowitz and Lichtenberg, 1993).

Given the environmental externalities associated with pesticide use, economists have often focused on a variety of mechanisms to reduce pesticide usage, including direct regulation and fees for use (Zilberman et al., 1991). In a related vein, economists have attempted to estimate the value of reduced pesticide usage (Maria Travisi et al., 2006), while elsewhere recognizing that prevailing incentives often make these reductions difficult to achieve (Cowan and Gunby, 1996). Of most direct interest for our purposes, IPM has emerged as an important means for reducing pesticides (more here). IPM includes decision rules based on economic thresholds (Fabre et al., 2007) (more in modeling section below?) and better knowledge and information (segue to next subsection).

The Economics of Agricultural Forecast Information

The value of information to producers and consumers and its impact on markets has intrigued economists for decades (e.g., Akerlof, 1970; Stigler, 1961). In agriculture, economists have studied the value of information to risk averse producers. Many of these explicitly model the value of information as a tool for reducing risk and decompose this value into mean and variance components (Byerlee and Anderson, 1982). While the degree of risk aversion directly shapes an individual’s valuation of new information in these models, there is not necessarily a positive correlation between the two “since the decision to acquire new information is itself often a risky decision” (Byerlee and Anderson, 1982).

Several studies have assessed the value of weather information to agricultural producers. One of the earliest such assessments highlighted the considerable potential value of rainfall forecasts in

September and October when the grapes are drying (Lave, 1963). Lave (1963) uses a partial equilibrium model to assess the value of better late season forecasts to an individual grower, then discusses how general equilibrium effects moderate this valuation. Babcock provides a more detailed analysis of producers' response to more accurate weather forecasts and illustrates how demand elasticity shapes this response (1990).

A few specific assessments of the value of weather information are worth highlighting. The link between weather forecasts and risk is especially strong in the case of frost since frost events can be forecasted and can devastate growers. Using a Bayesian decision making under uncertainty framework, Baquet, Halter and Conklin estimate the value of frost forecasts to orchard operators as a function of prices, forecast accuracy, and risk aversion (Baquet et al., 1976). Parker and Zilberman use survey data to assess the value of the California Irrigation Management System (CIMIS) and characterize producers that use this public weather information (1996). More recently, greater attention has been paid to the value of climate forecasts, which, in contrast to short-run weather forecasts, offer seasonal predictions of weather outcomes (Adams et al., 1995; Barrett, 1998; Mjelde et al., 1988).

Several studies have documented the potential value of disease and pest forecasts in the context of pest management decisions (Moffitt et al., 1986; Mumford and Norton, 1984; Swinton and King, 1994). Khanna and Zilberman study the potential environmental value of precision technology and the possibility of reduced pesticide applications (1997).

In contrast to this weather information and risk literature, this project will use high resolution disease forecasts and detailed records of pesticide application to model the disease treatment strategies with and without forecast information. This project will thus assess the value of forecast information in greater detail and at a finer resolution than has been done previously. For example, the project will use Pesticide Use Report (PUR) data collected by the California Department of Pesticide Regulation and historical spatial data on disease forecasts.

California Wine grapes, Powdery Mildew & the Powdery Mildew Index

Grapes contribute roughly 10 percent to California's annual $30 billion in farm sales and are the second most important agricultural crop in California. Wine grapes constitute an important part of total grape production, and the California wine industry has become a major component of the state's dynamic agriculture sector (Goodhue et al., 2008; Heien and Martin, 2003). Among California's wine grape growers, powdery mildew control is arguably the most important single management practice: they spend more each year controlling powdery mildew and still suffer more total losses to it than any other disease.

Grapevine powdery mildew can affect all succulent tissues on a grapevine, including the stem, fruit, and leaves, all of which can show characteristic symptoms of chlorosis in the area of infection and signs of the pathogen as powdery, web-like growth.[2] Powdery mildew is the most problematic fungal disease of grapevines in California and occurs in all grape growing regions of California. To some extent, it affects most wine, raisin and table grape varieties, but some varieties are extremely susceptible to powdery mildew, including Carignane, Thompson Seedless, Ruby Seedless, Chardonnay, Cabernet Sauvignon, and Chenin blanc.[3] Damages due to powdery mildew often depend on the timing of first infection – making early season control critical. Early fruit infections can cause stunting, scarring, or splitting of berries, and may increase the severity of bunch rots. The disease can also cause the epidermis to split, reducing the shelf life of table grapes, and can reduce the rate of photosynthesis and thus berry sugar content. Less than 5% disease on berries at harvest can cause off-flavors in wine (Stummer et al., 2005).

In their annual battle with powdery mildew, wine grape growers use a variety of preventative control options (Flaherty et al., 1992). Powdery mildew is generally controlled using an integrated program with regular treatments occurring every 7-21 days. The default treatment is sulfur dust, which is relatively cheap and can be applied at faster speeds, or micronized dry flowable sulfur. As conditions change throughout the season, growers often switch to more potent synthetic fungicides such as quinoxfen, DMI or Strobilurin fungicides. Sulfur is, however,

[2] The susceptibility of various plant parts to powdery mildew infection changes during the season. Fruit can become infected from just after bloom until the sugar content reaches 8 brix. Control practices are therefore essential during the early part of the season. Established fruit infections will continue to produce spores until the berries reach 12 to 15 Brix. Green tissues can be infected anytime during the growing season. The epidemiology of powdery mildew on grapevines is explained in detail elsewhere (Pearson and Gadoury, 1987; Sall and Wrysinski, 1982; Ypema and Gubler, 1997).

[3] Those that are less susceptible are Petite Sirah, Zinfandel, Semillon, and White Riesling.

commonly maintained in the program – either mixed in the tank or in rotation – to combat resistance or delay the onset of resistance to narrow spectrum synthetic fungicides.

Growth and development of powdery mildew is strongly affected by climatic conditions. It thrives under dry conditions with moderate temperatures (21 to 30°C), but spores and mildew colonies can be killed by extended durations of temperatures above 32°C. The fungus can be destroyed completely when air temperatures rise above 32°C for 12 hours or more (Ypema and Gubler, 1997). During continuous favorable temperature periods, the time between spore germination and production of spores by the new colony can be extremely rapid, occurring in as little as 5 days. The powdery mildew explosive increases that can occur from this very nonlinear climate relationship imply that treatment timing is essential to effective powdery mildew control: when optimal temperatures prevail during critical windows, a mistimed treatment can have catastrophic effects on the value of production at harvest. In this context, the potential value of disease forecasts is substantial.

Based on laboratory and field epidemiological studies of grapevine powdery mildew in California, a disease risk assessment model was developed and validated in all California grape production areas.[4] The UC Davis powdery mildew risk assessment model or Gubler-Thomas model forecasts ascospore release based on temperatures and leaf wetness periods to predict initial disease onset (Gubler et al., 1999; Thomas et al., 1994; Weber et al., 1996). Once infection has occurred, the model switches to a disease risk assessment phase and is based entirely on the effects of ambient temperature on the reproductive rate of the pathogen. The Gubler-Thomas model evaluates in canopy temperatures and assesses the risk of powdery mildew development using a powdery mildew index (PMI) that ranges from 0 (no risk) to 100 (extreme powdery mildew risk).[5] Low index values of 0-30 indicate the pathogen is not reproducing. An index of

[4] Similar disease forecasting models have been developed to predict the onset and severity of other plant diseases whose development is predictably influenced by climatic conditions, namely apple and pear scab, fireblight, botrytis bunch rot, wheat diseases and tomato diseases.

[5] After budbreak, there must be three consecutive days with a minimum of six consecutive hours of temperatures between 21 and 30°C for a powdery mildew epidemic to be initiated. The early season PMI therefore begins at 0 and increases by 20 points for each day with six or more consecutive hours in this optimal temperature range. Thus, after three consecutive days of six or more hours of optimal temperatures the PMI climbs to 60, with each of the three days contributing 20 index points. If after one day of temperatures in this range optimal temperatures do not persist for three consecutive days, the PMI reverts to zero. Once this early season requirement for three consecutive days of optimal temperatures is met, the index fluctuates between 0 and 100 based on daily temperatures for the remainder

40-50 is considered moderate and would imply a powdery mildew reproductive rate of approximately 15 days. Index values of 60-100 indicate that the pathogen is reproducing rapidly (as fast as every 5 days) and that the risk for a disease epidemic to occur is extreme. Since the mid 1990s, the PMI has been available in many regions as either a specific value for a single location or as a contour map for a defined space (see Figure 1) – typically via faxes or emails sent every day or two. Increasingly, the PMI is computed using on-site weather stations and software.

Per its original motivation, the PMI can potentially enable growers to sync their fungicide treatments more precisely with the actual disease risks that prevail in their vineyards. In particular, growers may postpone fungicide applications during extended periods with low PMI values. This potential value of the PMI has been demonstrated in field trials, which have shown that spraying according to the PMI can reduce fungicides "by 2-3 applications over the course of the growing season with equal or better disease control" (Gubler et al., 1999 p.10). The social, economic and environmental benefits of this reduction in fungicide use could be substantial. For example, it is estimated that the PMI could have reduced total sulfur applications by over one million pounds in 2003 (8 percent) if only a quarter of raisin growers followed the PMI (UC Agriculture and Natural Resources, 2005).

The magnitude of the actual benefits associated with growers' use of the PMI depends on two important factors (see Lybbert and Gubler, 2008). First, how growers make powdery mildew treatment decisions in the absence of the PMI provides a baseline from which the PMI response must be assessed. Although many assume that growers' baseline tendency is a calendar (or minimum interval) spray schedule, aggregate analysis of pesticide use reports in California suggest that these baseline schedules often deviate from a strict calendar spray regimen and may be partly conditioned on other factors (Epstein and Bassein, 2003). For example, prior to the development and diffusion of the PMI, plant pathologists typically told growers, "If you like the weather outside (mild and dry), then so does powdery mildew." Second, the actual benefits from PMI use obviously hinges on PMI adoption among growers, especially those responsible for

of the season: the PMI gains 20 points for each day of optimal temperatures and loses 10 points for each day that does not meet this six hour optimal temperature requirement. The PMI also loses 10 points if at any point during the day temperature rose to 35°C or higher for at least 15 min.

large shares of total fungicide applications. Despite favorable trials and widespread availability of high resolution PMI forecasts, only about half of California wine grape growers actively use the PMI to control powdery mildew, but adoption rates seem to be steadily increasing and are as high as 75% in regions such as Napa and Sonoma Counties with high value and susceptible wine grape varieties.

2 Model

Among the many existing economic models of pesticide use there are a few common concepts that are relevant to our analysis in this paper. The concept of an economic threshold, defined as the population level of the pest or disease at which the marginal benefit from damage prevented by the control program is equal to the marginal cost of realizing that population through a control program (e.g., Hall and Norgaard, 1973), is pervasive and foundational to the IPM movement. The role of uncertainty in disease or pest control is central in many models (e.g., Feder, 1979). Similarly, the formulation of expectations associated with the pest damage function and the updating of these expectations in response to new information is central to pest treatment decisions. Bayesian models have therefore been used to derive optimal crop disease control practices (Carlson, 1970). The dynamic dimensions of disease control are particularly difficult to incorporate explicitly into analytical models – and yet it is precisely these dynamic dimensions that make the economics of disease control interesting. Treatment intervals play a key role in our analysis and are inherently dynamic. In this section, we model this dimension but also incorporate product choice as an interrelated decision. Where others take a dynamic programming approach to model similar duration decisions (e.g., see Rust, 1987 for a model of engine replacement decision), our focus on a multidimensional response requires a numerical simulation approach.

The first dimension of the treatment choice is how often to treat or, posed as the real-time decision facing the grower, "How many days since my last treatment should I let pass before treating again?" At one extreme, which serves as a useful illustration in our model, a *naïve* grower can lock in a treatment calendar at the beginning of the season and stick with it throughout the season, regardless of daily changes to powdery mildew risk. While admittedly unrealistic, this is a common accusation leveled at growers. In contrast, a grower who receives the PMI might set out with a calendar in mind, but will constantly modify their intervals according to this information (and their confidence in it). For this *informed* grower, treatment intervals are determined real-time as the result of daily binary choices of whether to spray or wait to spray. In the derivation of our model, we continue to contrast these two prototypical growers – a *naïve* grower who receives no weather or powdery mildew risk information as the season unfolds and an *informed* grower who receives and uses the PMI – in order to highlight differences in optimal treatment responses that are attributable to the PMI.

The second margin of adjustment available to the grower in our model is chemical choice. There are several chemicals available for treating for powdery mildew, with different costs, protective strength, and environmental consequences. Chemical choice at least partially depends on a grower's perception of risk on any given day, either as determined by weather information or preconceived notions about the expected risk of infection at a given point in the season. Chemical choice can also be influenced by state imposed minimum intervals, which disallow treating the same area with the same chemical before waiting a mandated number of days.

The third and final dimension of the grower's treatment response in our model is the quantity, or dosage, of chemical to use on a given day. Even after deciding to spray a particular fungicide to treat for powdery mildew, a grower has some latitude to determine the dosage rate. Most pesticide labels, which contain information that is strictly regulated and requirements that are enforced (or, at least, enforceable), include a range of acceptable dosage rates. For example, Quintec, a popular product and the most common synthetic fungicide in our sample (see Table 1), includes a recommended range of dosage rates of 3 to 6.6 fluid oz per acre depending on the interval.

[At this time, the model only deals with the first two dimensions.]

For simplicity, we limit chemical choice to sulfur (X) and synthetic (Y) fungicides. We begin with an expected loss function for infection on plot *i* at day *t*. Expected loss is a function of the weather, PMI_{it}, the interval since the last sulfur treatment I_{it}^{X}, and the interval since the last synthetic treatment, I_{it}^{Y}. The loss function can be allowed to vary from plot to plot to reflect differences in microclimate and grape variety grown, and from day to day to reflect variable levels of risk throughout the season.

$$\pi_{it} = f_{it}(PMI_{it}, I_{it}^{X}, I_{it}^{Y}) \tag{1}$$

These intervals are determined by the historical use of these chemicals up to most recent treatment of each. This could conceivable go all the way back to the beginning of the period of powdery mildew risk, which we denote as *t* = 1.

$$\pi_{it} = f_{it}(PMI_{it}, I_{it}^{X}(X_{it}, X_{it-1,}X_{it-2,}, \dots, X_{i1}), I_{it}^{Y}(Y_{it}, Y_{it-1,}Y_{it-2,}, \dots, Y_{i1,})) \tag{2}$$

where X_{it} = 1 if X is sprayed on day *t* and zero otherwise (Y is defined analogously).

Under the simplifying assumptions that the grower is risk neutral (more below on how risk aversion might change growers' behavior in the model), and that damages incurred on any given day do not affect the probability of magnitude of future losses, the grower optimizes by limiting the sum of expected losses as chemical costs for the remainder of the growing season.

$$\underset{\boldsymbol{X}_{t_o},\dots,\boldsymbol{X}_T,\boldsymbol{Y}_{t_o},\dots,\boldsymbol{Y}_T,}{\mathrm{MIN}} \sum_{t=t_o}^{T} f_{it}(PMI_{it}, I_{it}^{X}(X_{it}, X_{it-1,}X_{it-2,}, \dots, X_{i1}), I_{it}^{Y}(Y_{it}, Y_{it-1,}Y_{it-2,}, \dots, Y_{i1,})) + \sum_{t=t_o}^{T}(p_X \cdot X_{it} + p_Y \cdot Y_{it}) \tag{3}$$

Finally, the grower is also subject to a minimum interval constraint for each chemical.

$$I_{it}^{X} \geq \underline{I^{X}}, I_{it}^{Y} \geq \underline{I^{Y}} \tag{4}$$

The problem can be solved analytically for a naïve grower, who determines a calendar at the beginning of the season based on preconceived expected value of PMI_{it}. For the informed grower, however, the problem is much more complicated because it involves a series of discrete choices that depend on continuously updated weather information. Therefore, the problem must be solved numerically using stochastic integer programming.

Uni-dimensional Response: Interval Choice Only

The goal of the numerical simulation is to compare the optimal spraying patterns for the naïve and informed growers under different conditions of weather, chemical efficacy, and chemical price. In particular, we examine how the changes in the optimal spraying pattern differ between a one-dimensional problem (when to spray only) and a two-dimensional problem (what to spray and when to spray). As a point of departure, we reduce the problem to a single dimension; the farmer has only one treatment option. We assume a functional form for f_{it} , which we assume is constant across farmers and time.

$$f(PMI_{it}, I_{it}^{X}) = \alpha \cdot PMI_{it} - \delta_X \cdot (\beta - I_{it}^{X})^{\gamma_X} \text{ where } 0 < \gamma_X < 1,\ \beta - I_{it}^{X} = 0 \ if \beta < I_{it}^{X} \qquad (5)$$

The weather variable PMI_{it} is intentionally analogous to the PMI: it ranges from 0-10 that moves in a random walk. We solve the model for a period of 10 days. In actuality, the period of powdery mildew risk spans much of spring and summer, but 10 days is sufficient to see patterns develop and change based on a grower receiving information of not.[6] The growers are constrained by a minimum interval constraint that does now allow them to spray on consecutive days, a stylized version of the common 7 to 14 day regulated minimum interval. To start the model, we assume that the 10 day interval is preceded by a period (t=0) of zero powdery mildew risk.

For both the *naïve* and the *informed* grower, we solve the problem under conditions of a high PMI trajectory and a low PMI trajectory. The results of this simulation are shown in Table 2. The *naïve* grower does not have any expectations what PMI_{it} will be on any given day, and therefore solves their spraying problem under a constant expectation of $E[PMI_i] = 5$. Therefore, the optimal decision is a calendar spray that can be determined at the beginning of the growing season. Her solution to the problem will be the same under both trajectories, spraying every other day starting on the first day, but will result in different levels of expected damages. The *informed* grower responds to the PMI and consequently exhibits different behavior under the two trajectories. When the PMI is low, she stretches intervals and sprays 4 instead of 5 times. This is precisely the logic behind the inception of the PMI, but – as we will see – this response hinges on our assumption that growers only have one response (interval) at their disposal. Under the high PMI trajectory the informed grower sprays every other day since the minimum interval constraint does not allow her to spray more frequently, and the two growers behave identically.

[6] The problem entails a discrete choice variable for each day of the program. Since the optimization software (GAMS in this case) cannot use derivatives to search, it must choose between all available alternative combinations that satisfy the constraints. The curse of dimensionality quickly becomes a major barrier when more days are added.

Two Dimensional Response: Interval & Chemical Choice

When a farmer has two chemicals of differing strengths and duration of coverage, the problem becomes:

$$f(PMI_{it}, I_{it,}^{X} I_{it}^{Y}) = \alpha \cdot PMI_{it} - \delta_X \cdot (\beta - I_{it}^{X})^{\gamma_X} - \delta_Y \cdot (\beta - I_{it}^{Y})^{\gamma_Y} \text{ where } 0 < \gamma_X, \gamma_Y < 1, \quad (6)$$

$$\beta - I_{it}^{X} = 0 \; if \beta < I_{it}^{X}, \beta - I_{it}^{Y} = 0 \; if \beta < I_{it}^{Y}$$

Here we use a similar simulation as before for the naïve and informed growers, but allow them to adjust chemical type in addition to spraying intervals (see Table 2 bottom panel).

The naïve grower once again uses the same strategy under the low and high PMI trajectories, but the unique strategy is very different from the one-dimensional case. She delays treatment until the fifth day, but treats with the much stronger chemical Y. On the ninth day she follows with a treatment of the less potent chemical X. Under the low PMI trajectory the informed farmer only uses chemical Y, but sprays only twice (as opposed to four times in the one-dimensional case). Under the high PMI trajectory she sprays five times, twice with chemical X and three times with chemical Y. In the one dimensional case she also sprayed five times, but only with chemical X.

In sum, once we allow for a two dimensional response, use of the PMI no longer leads to stretched intervals (on average) when the PMI is low and seems to lead to more frequent use of the more potent treatment. This result is robust across a range of parameter values (the final parameter values were chosen because they allow the model to converge across all variations of the model). While the above model assumes growers are risk neutral, assuming they are risk averse is likely to further magnify this result. In particular, it may introduce an asymmetry in the PMI response since growers are likely to respond more strongly to information of high risk than they are to information of low risk. Although this simulation is obviously a stylized version of what wine grape growers face in reality, the core insight is important and will be tested empirically in the analysis below.

3 Data

The empirical merit of our analysis stems largely from the spatial and temporal resolution of the data we use to estimate growers' response to the PMI. By merging data from multiple sources, we construct a high resolution panel dataset that tracks daily fungicide use and yearly PMI use among roughly 100 wine grape growers from 1996 to 2007 and includes daily PMI forecasts for this period.

As the starting point for constructing this dataset, we conducted an online survey of California wine grape growers in January and February 2008. The survey included questions on disease management generally and powdery mildew specifically, on vineyard and vineyard manager characteristics, and on their use of the PMI. Members of the California Association of Wine grape Growers and several other state and local grape growers' associations were invited to participate in the survey. Ultimately, 108 wine grape growers participated in the survey. Nearly two-thirds of our surveyed growers have used or currently use the PMI to some degree (see Figure 2). This seems consistent with Californian wine grape growers generally, who tend to rely on the PMI more than table and raisin grape growers (see Lybbert and Gubler, 2008 for a preliminary analysis of the forecast adoption decision). In the present analysis, we include 67 growers from seven major wine grape growing counties for which we had adequate PMI data (more below): Fresno (5 growers), Madera (5), Mendocino (4), Napa (8), San Joaquin (9), San Luis Obispo (17), and Sonoma (19).

We obtained from agroservices providers[7] daily PMI values for locations near our surveyed growers. In some cases, we reconstructed the PMI from raw hourly temperature data collected from weather stations near these growers. Most of these PMI data begin when the model was first used in 1996 and continue until 2007. We matched growers in our survey to the nearest station for which we have PMI data. The mean distance from growers central location to the nearest station is 13 km. To capture intervals between pesticide applications, we generated a data point for each day of the grape growing season for which PMI data was available (typically March through October) from 1996 to 2007 for each plot managed by a grower in our survey sample, resulting in 940,065 observations.

[7] We thank Terra Spase and AgUnlimited for providing these data for several regions in northern California. In central and southern California, we accessed the PMI or raw temperature data with the help of the University of California Statewide IPM Program and Jenny Broome.

The unprecedented temporal resolution of our data stems from the rigorous pesticide use reporting system administered in California by the Department of Pesticide Regulation (DPR). In this system, growers must obtain a pesticide use permit before applying any pesticides and then must then file a pesticide use report (PUR) with their respective county agriculture commissioner each time they apply a pesticide. These PURs are then aggregated across counties by the DPR and are publicly available via the DPR website (see Epstein, 2006 for more details about the PUR system). Each PUR contains the grower's county-level grower ID, which allowed us to match our surveyed growers to their PURs, along with an impressive battery of other details, including the crop treated, the product used, its active ingredient, the application rate, the number of acres treated, and the total size and spatial location of the plot. In our analysis, we use plot-level PURs to understand growers' powdery mildew treatment decisions; each grower in our survey has an average of five plots during years of our analysis. One aggregate analysis of PUR data and the potential impact of IPM on pesticide usage precedes our grower-specific analysis (Epstein and Bassein, 2003).[8] The value of our analysis derives from leveraging the temporal resolution of the PUR data by integrating it with spatial PMI data and grower survey data that includes PMI usage over time, which allows us to directly test the impact of the PMI on growers' powdery mildew strategies and on total pesticide usage.

There are, however, a number of limitations with PUR data, many of which have been explored elsewhere (add REFS). Two limitations are worth mentioning here. First, PURs do not include *why* the grower applied the pesticide (e.g., the pest or disease targeted). Fortunately, powdery mildew treatment can be inferred quite accurately based on the product used since most of the fungicides used to control powdery mildew focus narrowly on this disease. We used data from the UC IPM Program on the efficacy of different fungicides for grapes[9] and consultations with plant pathologists to identify powdery mildew treatment. The most commonly used powdery mildew products in our PUR data are shown in Table 1. Second, growers choose their own plot labels and sometimes change their plot labels from one year to the next, which makes it difficult to track plot trends over years. While the consistency within a given year is sufficient to enable us to construct treatment intervals at the plot level and thereby use plots as our unit of analysis,

[8] Several other inquiries – including both environmental and human health related – have used PUR data (e.g., Davidson, 2004; Reynolds et al., 2002).
[9] Available at http://www.ipm.ucdavis.edu/PMG/r302902111.html (accessed 10 March 2010).

we are unable to control for unobservable plot characteristics over time (e.g., with plot fixed effects).

Since descriptive statistics from our survey data are presented and discussed elsewhere (Lybbert and Gubler, 2008), we focus here on a brief statistical description of the interval and fungicide use tendencies of the growers in our sample (Table 3). From these unconditional comparisons, there appear to be some differences between those receiving the PMI and those not receiving it. Those getting the PMI seem to have longer intervals after spraying sulfur, but are statistically indistinguishable from their non-PMI counterparts when it comes to synthetic intervals.

4 EMPIRICAL MODEL & RESULTS

The objectives that guide our empirical analysis are twofold. First, we aim to test whether wine grape growers respond to the PMI by adjusting their powdery mildew treatment strategies and to characterize any such response along three potential margins of adjustment: treatment timing, product choice, and dosage rate. Second, we aim to assess the net environmental impact of any PMI response, which is complicated once we allow for simultaneous adjustment on more than one margin. For example, PMI users may – as its inventors intended – stretch intervals when the PMI is low, but they may also increase dosage rates when it is high. Furthermore, growers may respond asymmetrically to changes in the PMI. They may respond aggressively and promptly to increases in the index, while being relatively unresponsive to a low PMI. Throughout our analysis we leverage the panel structure of our data. Thus, in addition to comparing the treatment tendencies of growers using the PMI to those not using the PMI, we can also focus exclusively on growers who initially did not use it but switched to using the PMI during the coverage of our data. In the latter case, growers serve as their own counterfactual in a before-after identification approach.

A. How do growers respond to the PMI?

To characterize growers' response to the PMI, we rely heavily on non-parametric estimation in order to allow flexibility and to facilitate interpretation of the relationship between PMI use and the three margins of adjustment. We begin with a simple conditional mean estimation that non-parametrically maps growers' treatment intervals on PMI values. As described above, the hypothesized relationship for PMI users is negative, which would suggest that users safely stretch intervals when the PMI is low but tighten the intervals as it increases. We compute plot-level powdery mildew treatment intervals using the PUR data.[10] We compare each interval to the minimum interval that corresponds to the previous product used on that plot in order to construct an interval stretching variable. We then non-parametrically regress this variable, the number of days a grower stretches his powdery mildew interval, on the value of the PMI on the day the grower chooses to end the interval. Figure 3 shows this regression for all regions and all growers (right) and suggests that growers using the PMI seemed to stretch intervals relative to non-users when the PMI was low, but also (somewhat surprisingly) when it was high. The right-hand panel provides a cleaner comparison by focusing only on growers who switched to using the PMI ("switchers" hereafter). In this panel, there is no clear interval response to the PMI when growers begin using it. If anything, after adopting the PMI, growers tighten their intervals across the board. Furthermore the relationship tends to be positive rather than negative. Since powdery mildew treatment and viticulture more generally can change dramatically from location to location, we display the same non-parametric regression for Napa and Sonoma county growers alone in Figure 4. Again, PMI users seem to run tighter intervals than non-users regardless of the PMI – although both types of growers apparently respond to the index (recall the rule of thumb "if you like the weather, then so does powdery mildew").

Next, we use analogous non-parametric conditional mean regressions to assess the second margin of adjustment, fungicide choice. We do this by computing each grower's probability of spraying sulfur on a given day conditional on the grower choosing to treat for powdery mildew that day. Figure 5 (top) shows these sulfur probability regressions, which suggest that PMI users (switchers) are significantly less likely to spray sulfur when the PMI is high than their non-user counterparts (selves). For more potent synthetic fungicides the pattern is flipped: PMI use seems to induce an offsetting increase in the probability of spraying synthetic fungicides when the PMI is high. This pattern is even more pronounced when we zoom in on Napa and Sonoma growers (Figure 6): PMI-users are nearly three times more likely to spray synthetic fungicides when the PMI is high than their counterparts. To emphasize how spatially heterogeneous these responses

[10] Details of our construction of these intervals, which are complicated, are forthcoming as an appendix.

are, Figure 7 shows these fungicide response regressions for Mendicino growers, which suggest a much more muted response along this margin.

[We are in the process of estimating similar regressions for dosage rate response.]

While the non-parametric conditional mean regressions are a useful first step, there are many factors that influence growers' powdery mildew treatment that are not captured by these regressions. We are in the process of estimating a semi-parametric model that will enable us to control for a host of other factors and more cleanly identify the impact of the PMI on these margins of adjustment. Specifically, we are estimating a semi-parametric smooth coefficient model (Li et al., 2002) of the following form:

$$Interval_{ijt} = \alpha(PMI_{it}) + \beta(PMI_{it})UsePMI_{it} + \mathbf{x_{ijt}}'\boldsymbol{\varphi} + \varepsilon_{ijt} \tag{1}$$

where $\alpha(PMI_{it})$ is a stand-alone non-parametric function, $\beta(PMI_{it})$ is a non-parametric function that allows the impact of PMI use on treatment intervals to vary flexibly as the PMI changes, and $\mathbf{x_{ijt}}$ is a vector of control variables that include grower, year and county fixed effects, dummy variables for relevant sub-seasons for grower *i*'s location (i.e., bud break, shoot growth, etc.), and an estimate of grower's expected value of the current season grape harvest at the plot-level. [Results are forthcoming.]

So far we have focused on non-parametric techniques to understanding growers' response to the PMI. We have also estimated several parametric models to test this response. Specifically, we have estimated a selection model in which (i) growers first decide whether to spray for powdery mildew on a given day and then, (ii) conditional on having decided to spray, they decide what product to use. This approach allows us to compare PMI users to non-users in both stages. The results of this parametric approach shown in Table 2 corroborate the non-parametric results above. Because of the interactions and quadratic terms in this specification, the parametric results are difficult to interpret as separate coefficients. We use graphical depictions of these results instead. Figure 7 uses these results to graph the difference between PMI users and non-users in their probability of spraying (left) and in the efficacy of the product used conditional on choosing to spray (right) as a function of the PMI. These results suggest a clear pattern: Relative to non-users, PMI users are actually less likely to spray as the PMI gets high, but more likely to shift to more potent, more effective (and more expensive) treatments. Both dimensions of this pattern, which is robust to including only switchers, stem from PMI users product choice response to the PMI. They shift to more effective products as the PMI increases. These synthetic fungicides offer longer protected intervals, which imply that the probability of spraying on a given day actually decreases.

B. What is the net environmental impact of growers' multidimensional PMI response?

Our analysis allows for growers to respond to the PMI by adjusting their intervals, product choice and (ultimately) dosage. We find evidence that changing their product choices is at least as important as a margin of adjustment for growers as is altering their treatment intervals. Given this two dimensional response, it is impossible to predict the environmental impact of the PMI without a taking into account both dimensions (all three) simultaneously. To do this we use the Pesticide Use Risk Evaluation (PURE) model under development by Zhang and Zhan at the Department of Land, Air and Water Resources at UC Davis. This model merges plot level PUR data with physical, soil, topographical, and meteorological characteristics to compute a pesticide use risk index for four dimensions: surface water, groundwater, soil, and air (see Figure 8). Risk scores from these four dimensions are then aggregated into an aggregate risk index. We use these risk scores, which are normalized as an index ranging from 0 to 100, as indicators of the overall environmental impact of a particular grower's pesticide usage in a given year. In this way, we can test whether adopting the PMI changes a grower's pesticide risk scores as a way to estimate the net environmental impact of growers' multidimensional PMI response.

With the collaboration of Zhang and Zhan, we have PURE risk scores for 69 of our surveyed growers. To assess the impact of PMI adoption on these scores, we estimate the following model

$$Risk_{ijt}^{z} = \beta_0 + \beta_1 GetPMI_{it} + \beta_2 UsePMI_{it} + \gamma_t + \mu_j + (\upsilon_i + \varepsilon_{ijt}) \qquad (2)$$

where z={aggregate, surface water, groundwater, soil, air}, *GetPMI* is a dummy variable indicating whether grower *i* received the PMI in year *t*, *UsePMI* is a dummy variable indicating whether a grower used the PMI 'heavily' or 'often' in that year, γ_t is a year fixed effect, μ_j is a county fixed effect, and υ_i is a grower random effect. Before discussing the results, note that the

$Risk_{ijt}$ scores we use in equation (2) include all pesticides used by grower *i* in county *j* in year *t* – i.e., they do not focus narrowly on powdery mildew treatment. Furthermore, as is apparent in Figure 3, several of the environmental factors included in these scores lie outside growers' control. Combined these two features should dilute the relationship between the PMI variables and risk scores in equation (1) and thereby strengthen the test of the PMI coefficients in (1).

Table 5 contains the estimation results from this specification. Several specific results are worth highlighting. First, growers receiving the PMI tended to have slightly lower risk scores, although this is mostly statistically insignificant. Second, conditional on receiving the PMI, those using it heavily or often in a given year had slightly *higher* risk scores. While this result is at least weakly significant for all but the groundwater risk model, it is also much smaller in magnitude than general decline over time in risk scores that is evident in the year fixed effects. Still, it is insightful that even after controlling for year and county unobservables the net environmental impact of using the PMI appears to be slightly negative. Furthermore, this impact increases in both magnitude and statistical significance when we include only those growers who adopted the PMI during the 1996-2007 window. This suggests that the result is robust and is not due to inappropriate comparisons between growers. It should be noted that this may be driven by a distinctly asymmetric response on the part of PMI users: they may respond aggressively when the PMI is high, but pay little attention to the PMI when it is low. This asymmetry may be magnified slightly by the model itself, which is understandably conservative (false negatives are potentially more costly to growers than false positives).

5 Conclusions

We began this paper with the observation that how and how well growers manage the risks inherent in agriculture has direct welfare implications for producers and consumers at both local and societal levels. While better weather, pest and disease forecast information are rapidly disseminating among producers and are often touted as promising inputs to production and risk management, little is known about how this new information actually shapes producer behavior in practice. In this paper, we argue that better forecast information can certainly benefit growers and improve their capacity to manage disease and pests effectively, but we must jointly consider the various margins of adjustment available to growers in order to properly understand their response to this improved information.

Using the case of California wine grape growers and high resolution panel data that includes plot-level powdery mildew treatments, we characterize growers' response to a popular powdery mildew risk model that generates forecast in the form of a daily risk index (PMI). Our analysis suggests that growers using the PMI primarily adjust their choice of product in response to the PMI by switching to higher potency synthetic fungicides when the risk is high. Since these products have longer minimum intervals, this implies that – if anything – PMI users have longer intervals as the PMI increases. While this core empirical result is robust across a variety of specifications (both parametric and non-parametric), we also find substantial spatial heterogeneity, which is logical given the dramatic spatial differences that exist among wine grapes and wine grape growers (e.g., differential susceptibilities of grape varieties to powdery mildew, differential harvest values, etc.).

Our preliminary results suggest that the net environmental impact of this documented multi-dimensional response to the PMI may actually be negative, although we emphasize that these are preliminary results. Futhermore, it is important to note that the magnitude of this effect is small compared to the general improvements in wine grape growers' environmental impact over the past several years.

Finally, although we have been able to characterize growers' response to the PMI, we are unable to document the impact of their response on disease control. Based on widespread evidence from field trials, we presume that PMI users are more effective at controlling powdery mildew in their vineyards as a result of their responses to the PMI. Indeed, our survey evidence suggests that growers using the PMI value it as an important tool in their decision making. Without data from our growers on the efficacy of changes in their treatment strategies, we are unable to completely assess the value of the PMI from the growers' perspective.

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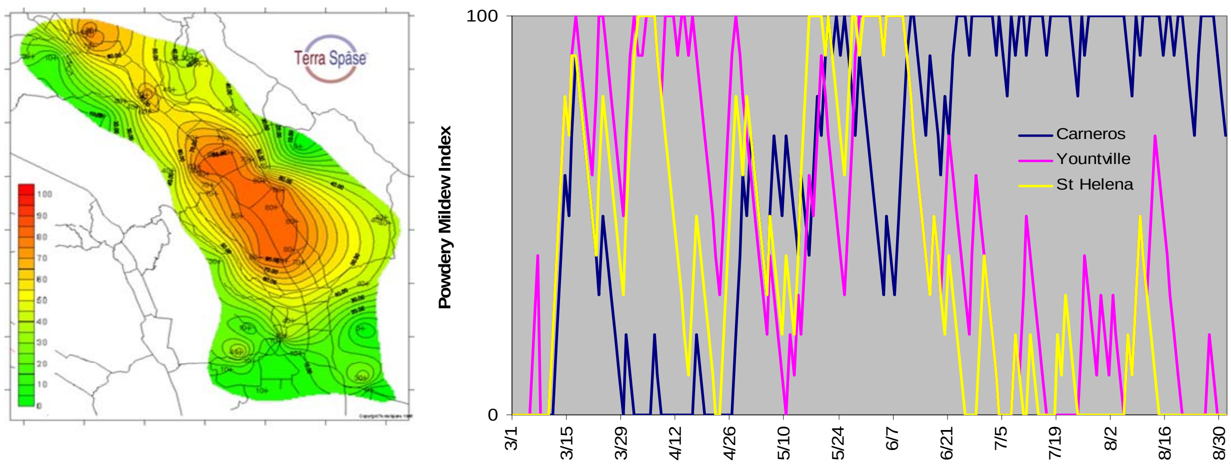

Figure 1 Spatial PMI contour map for Napa County (18 June 1996; left) and evolution of PMI for three sites in Napa County (2007; right) (Source: Terra Spase)

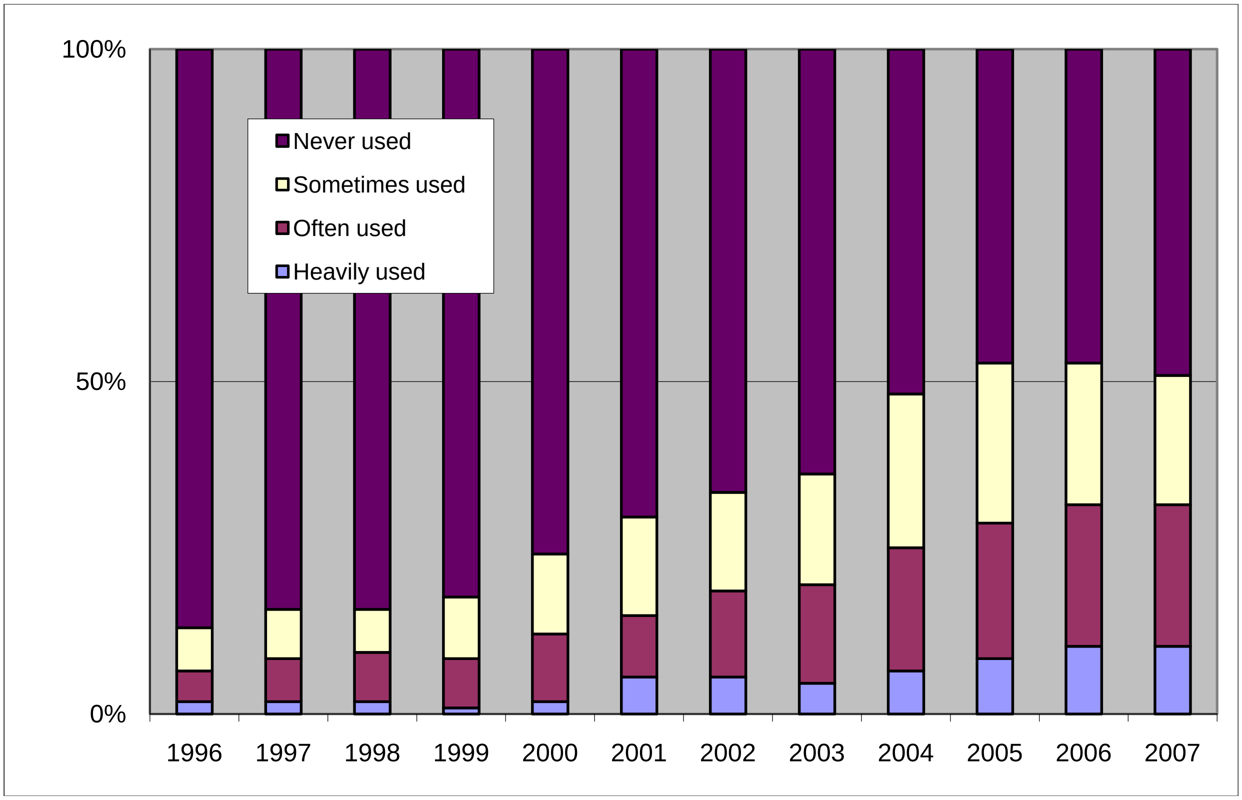

Figure 2 Intensity of PMI use over time for surveyed growers

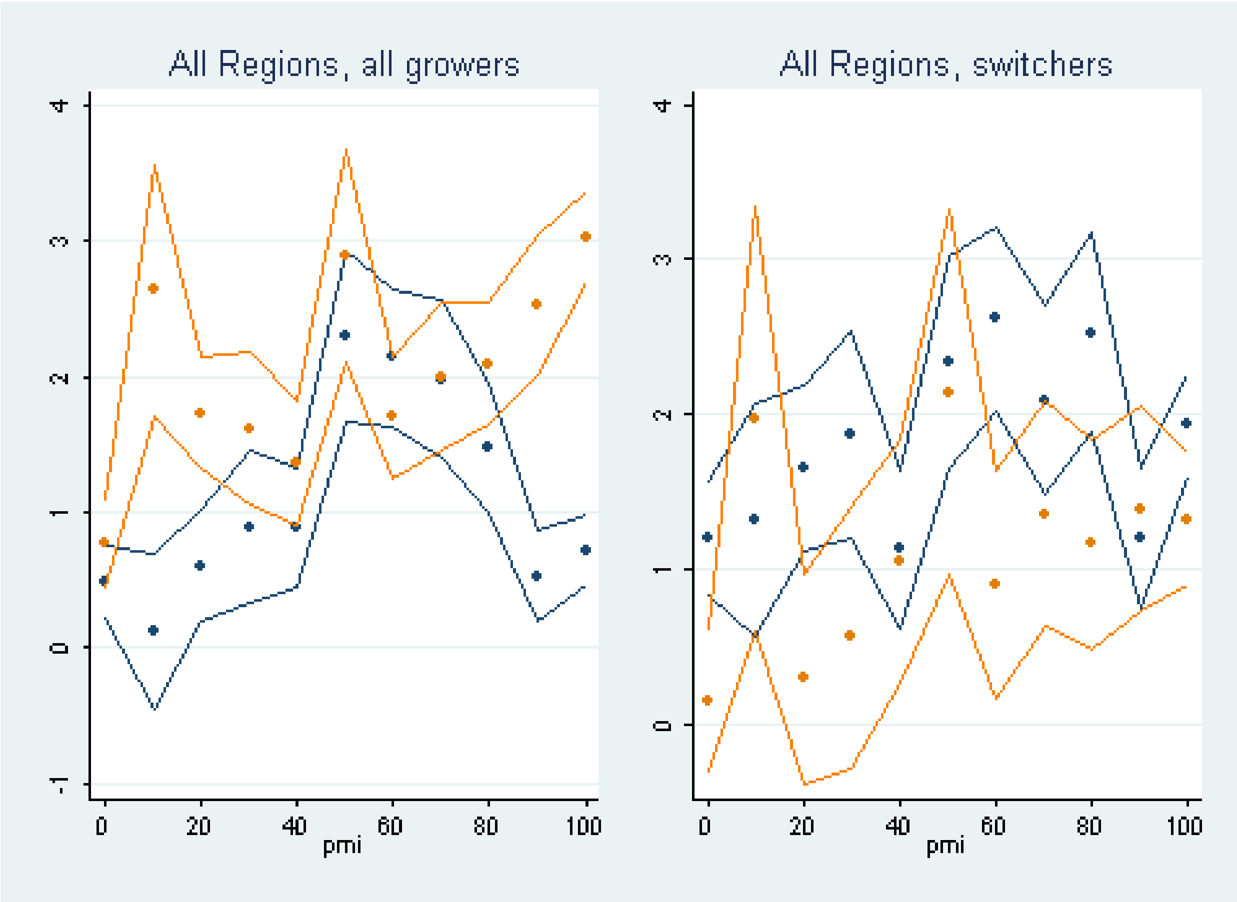

Figure 3 Non-parametric regression (mean and 95% confidence intervals) of interval stretching on the PMI (blue= non-PMI users, orange=PMI users)

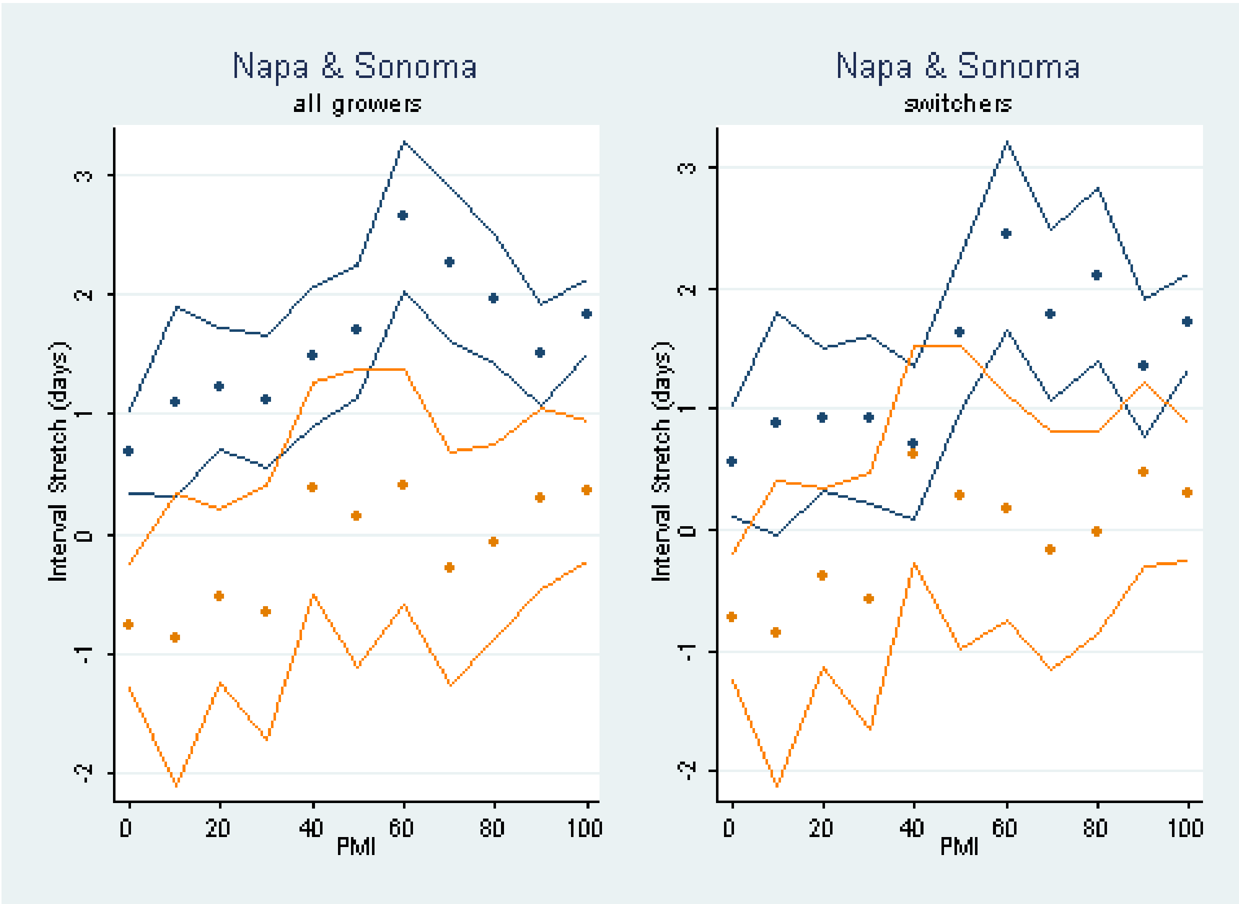

Figure 4 Non-parametric regression of interval stretching on the PMI for Napa and Sonoma growers (blue= non-PMI users, orange=PMI users)

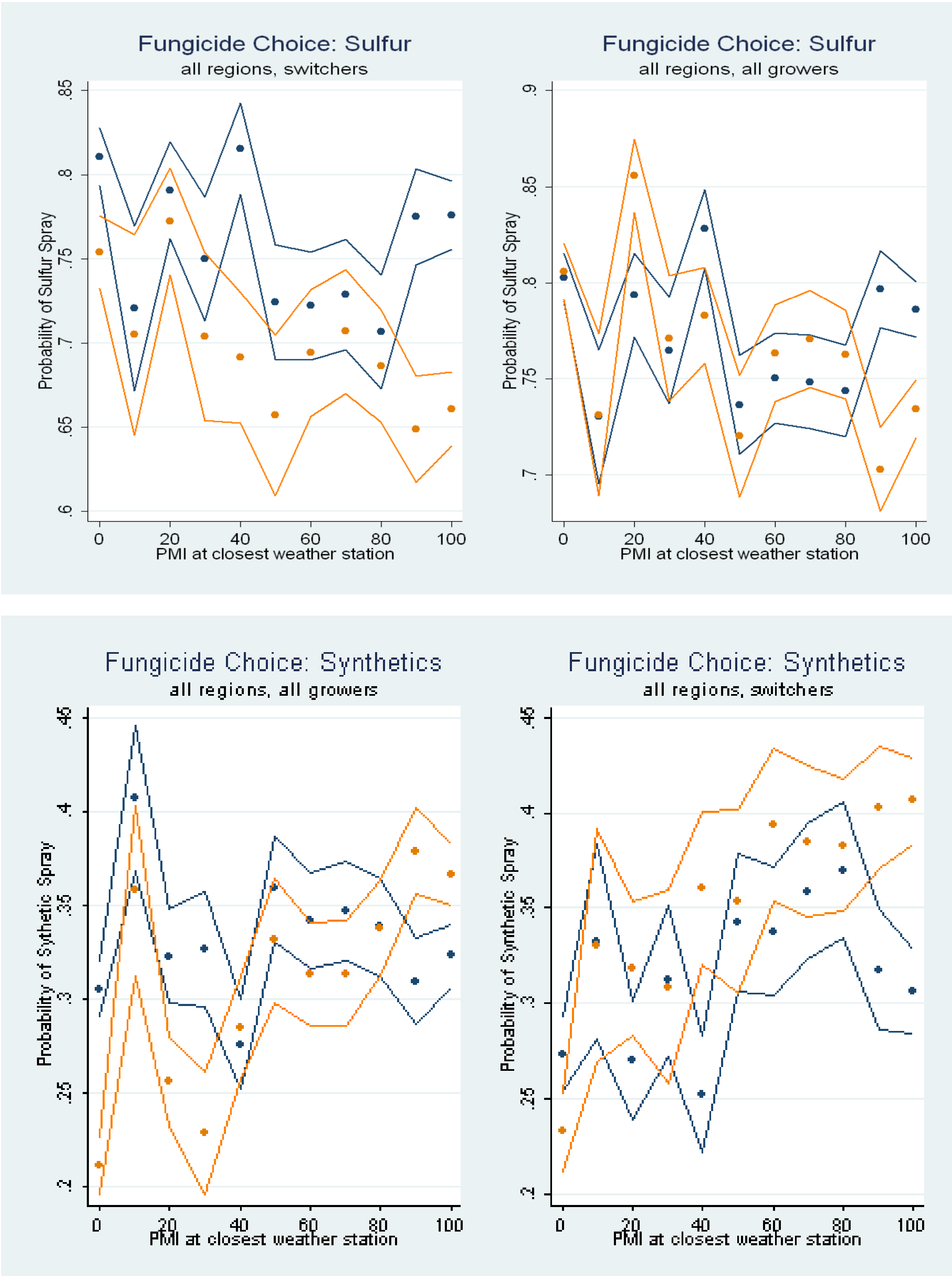

Figure 5 Non-parametric regression of probability of spraying sulfur (top) and synthetic fungicides (bottom) on the PMI (blue= non-PMI users, orange=PMI users)

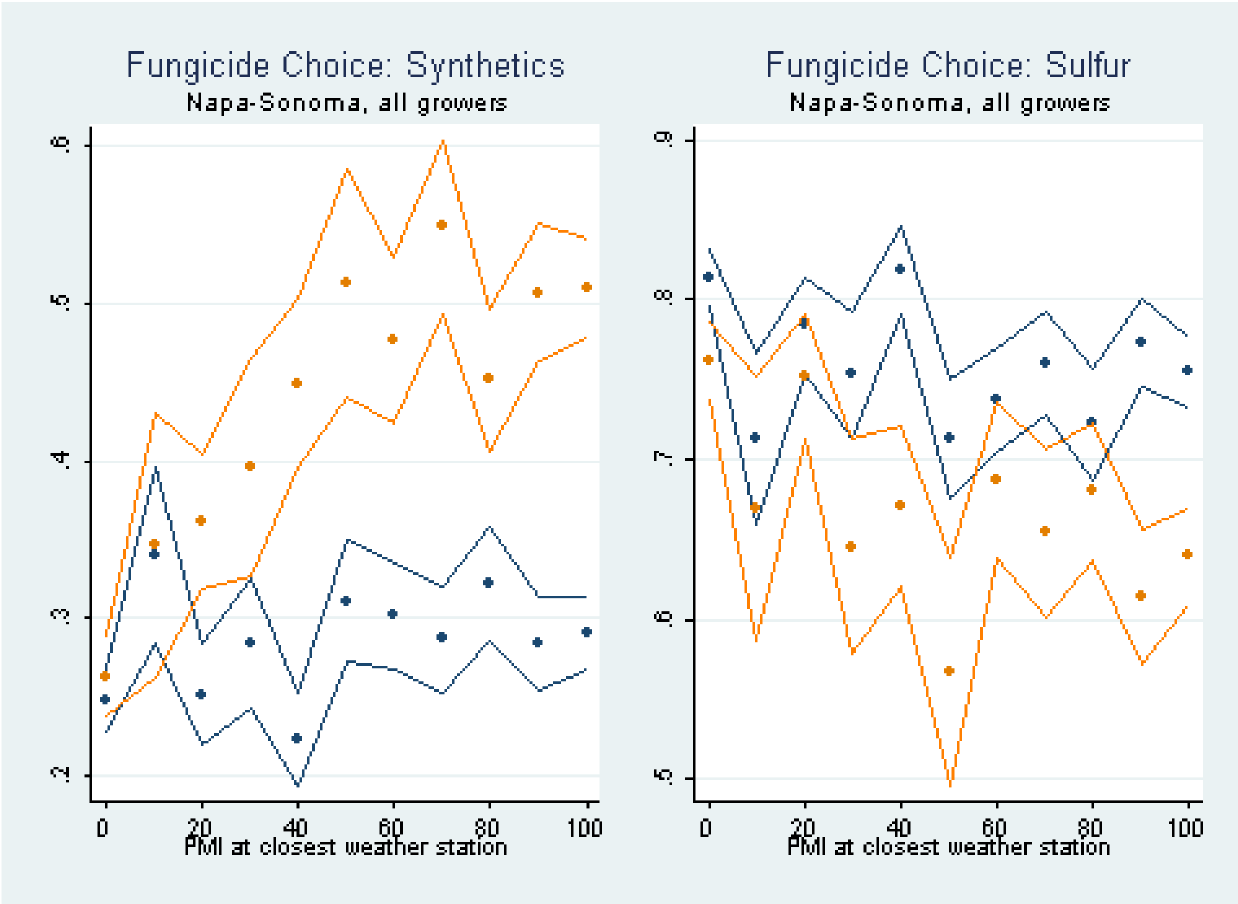

Figure 6 Non-parametric regression of probability of spraying sulfur and synthetic fungicides on the PMI for Napa and Sonoma counties (blue= non-PMI users, orange=PMI users)

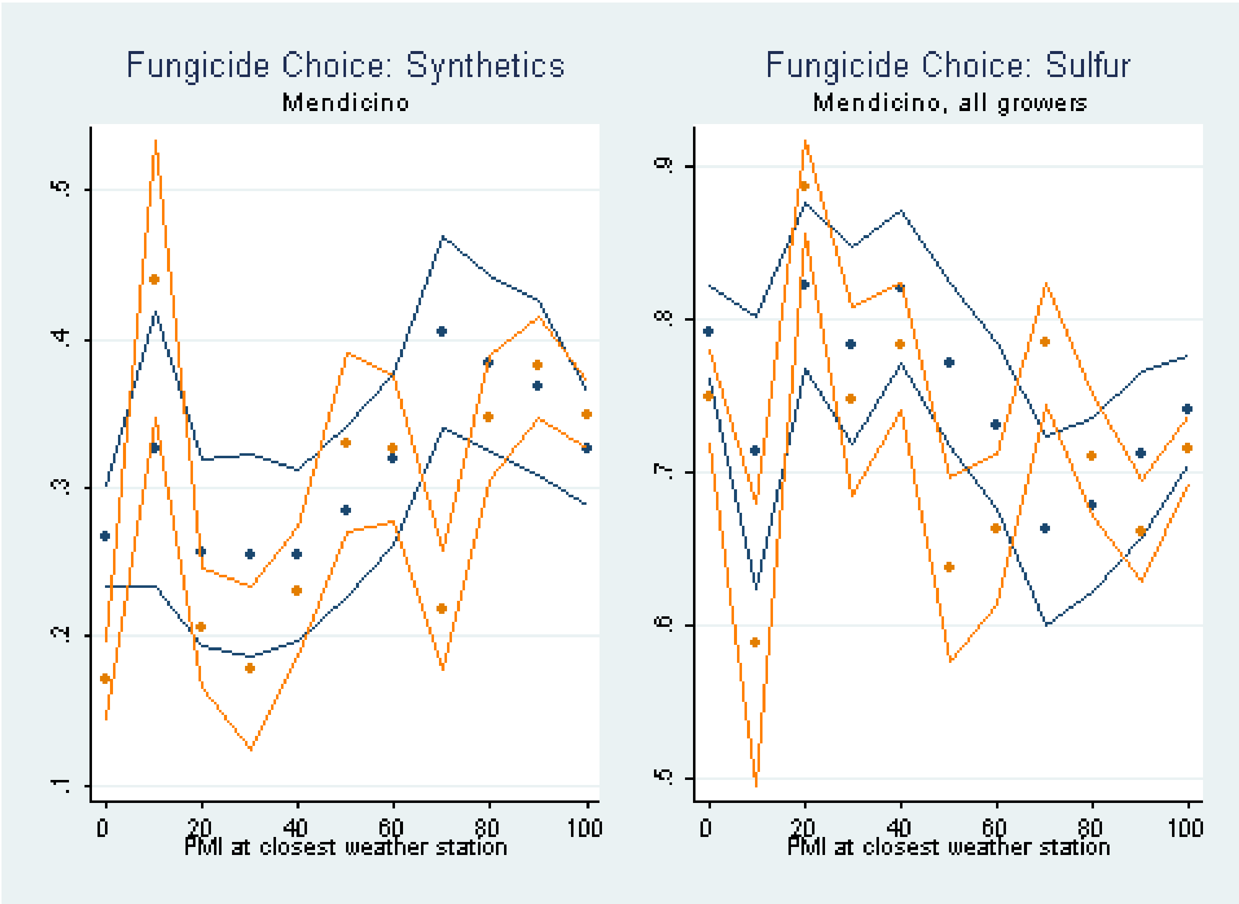

Figure 7 Non-parametric regression of probability of spraying sulfur and synthetic fungicides on the PMI for Mendicino county (blue= non-PMI users, orange=PMI users)

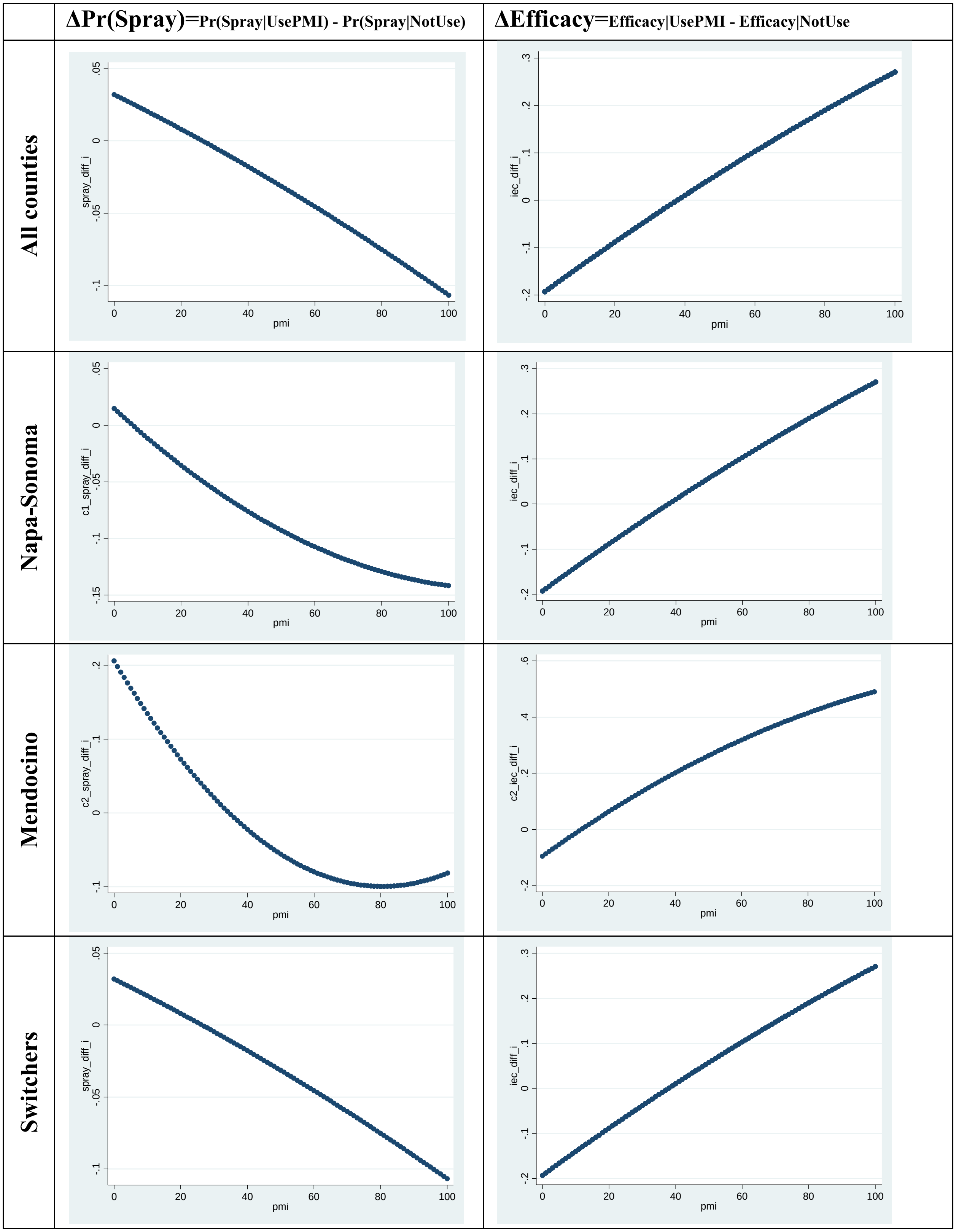

Figure 8 Difference in probability of spraying and choice of product (efficacy) between PMI users and non-users implied by parametric selection model estimation results

PURE

		Surface Water	Groundwater	Soil	Air
Physical-chemical	Sorption Coefficient	*	*		
	Henry's Law Constant		*		
	Half Life in Soil	*	*	*	
	Half Life in Water	*			
	Emission Potential				*
Toxicity	Toxicity to Aquatic Organisms	*			
	Toxicity to Earthworm			*	
	Acceptable Daily Intake		*		
Soil Property	Bulk Density	*	*	*	
	Organic Carbon Content	*	*		
	Sand Content	*			
	Hydrology Group	*			
	Field Capacity		*		
Topography	Ground Slope	*			
	Distance to Surface Water	*			
	Groundwater Table		*		
Meteorology	Annual Rainfall	*	*		
	Maximum Daily Rainfall	*			
	Temperature	*	*	*	
Miscellaneous	Crop Type	*	*	*	
	Application Time	*	*	*	
	Application Intensity	*	*	*	*

Figure 9 Elements in the Pesticide Use Risk Evaluation (PURE) model

Table 1 Most frequently used products for treating powdery mildew among our surveyed growers, 1996-2007

Efficacy	Toxicity According to Label*	Product Name	Minimum Interval	Frequency of Use for Powdery Mildew Treatment
High	*Caution*	PRISTINE FUNGICIDE	14	9%
	Caution	QUINTEC	14	7%
	Warning!	RALLY 40 WSP	10	5%
	Caution	FLINT FUNGICIDE	10	4%
	Warning!	ELITE 45 WP FOLIAR FUNGICIDE	10	3%
	Caution	JMS STYLET-OIL	-	2%
	Caution	ABOUND FLOWABLE FUNGICIDE	14	1%
Medium	*Caution*	SULFUR products	7	58%
Low	*Caution*	KALIGREEN	-	2%
	Caution	SERENADE	7	1%
	Caution	SONATA	7	0.4%

* Three levels of toxicity are indicated on the label: highly toxic (*Danger!*), moderate toxicity (*Warning!*) and low toxicity (*Caution*).

Table 2 Results of stochastic integer programming model: (a) interval stretching when one dimensional choice (interval) is assumed, (b) risk of slightly higher damages from interval stretching, and (c) PMI-induced shift to higher potency (efficacy) chemicals.

Interval Only	**Day:**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**# Sprays**	**Cost**	**Crop Damages**
	Low PMI (3.6 avg)	5	3	2	2	3	3	4	5	4	5			
Naïve	Spray X	1	0	1	0	1	0	1	0	1	0	5	10	(b) 31.1
Informed	Spray X	1	0	0	0	1	0	1	0	1	0	(a) 4	8	33.6
	High PMI (8.4 avg)	5	3	2	2	3	3	4	5	4	5			
Naïve	Spray X	1	0	1	0	1	0	1	0	1	0	5	10	252.3
Informed	Spray X	1	0	1	0	1	0	1	0	1	0	5	10	252.3
	$\alpha = 5, \gamma_X = 0.8, p_X = 2, \delta_X = 3$													
Interval & Chemical	**Day:**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**# Sprays**	**Cost**	**Damages**
	Low PMI (3.6 avg)	5	3	2	2	3	3	4	5	4	5			
Naïve	Spray X	0	0	0	0	0	0	0	0	1	0	(c) 1	5	0
	Spray Y	0	0	0	0	1	0	0	0	0	0	1		
Informed	Spray X	0	0	0	0	0	0	0	0	0	0	0	6	7.6
	Spray Y	0	0	0	0	0	0	1	0	1	0	2		
	High PMI (8.4 avg)	5	3	2	2	3	3	4	5	4	5			
Naïve	Spray X	0	0	0	0	0	0	0	0	1	0	1	5	100.8
	Spray Y	0	0	0	0	1	0	0	0	0	0	1		
Informed	Spray X	0	0	0	1	0	0	1	0	0	0	2	13	34.2
	Spray Y	0	0	1	0	1	0	0	1	0	0	3		
	$\alpha = 5, \gamma_X = 0.8, p_X = 2, \delta_X = 3, \gamma_Y = 0.7, p_Y = 3, \delta_Y = 6$													

Table 3 Descriptive statistics for fungicide use and intervals for the wine grape growers in our survey

Variable	Combined	Get PMI	Do not get PMI
Percentage of sprays with sulfur	47.6%	47.1%	48.0%*
Percentage of sprays with synthetics (sterol inhibitors or strobulurins)	55.0%	53.3%	56.2%***
Percentage of sprays with sterol inhibitors	42.9%	32.2%	50.3%***
Percentage of sprays with strobulurins	12.67%	21.9%	6.3%***
Interval after using sulfur	12.27	13.8	11.1***
Interval after using synthetic	15.0	14.6	15.2
Stretching past recommended interval (next treatment with any chemical) in days	-2.22	-2.06	-2.33

***0.01, **0.05,*0.1 indicates statistical significant differences between those receiving the PMI and those not receiving it.

Table 4 Selection equation results

	Spray Selection Equation (Probit)		Efficacy Choice (Ordered Probit)	
	Coef.	StdError	Coef.	StdError
UsePMI	0.143218	0.01742	-0.33421	0.226441
PMI	0.00417	0.000515	-0.01288	0.006587
PMI^2	-1.9E-05	4.77E-06	0.000057	0.000031
PMI_{t-1}*UsePMI	-0.00285	0.000667	0.009735	0.004664
PMI_{t-1}^2*UsePMI	8.44E-06	6.24E-06	-3.6E-05	0.000019
Last spray (days)	0.139528	0.002796	-0.46655	0.218816
Last $spray^2$(days)	-0.00479	0.000118	0.016947	0.007516
Bud break	0.099014	0.017114	-0.49647	0.159821
Shoot growth	0.211024	0.012738	-0.64989	0.329572
Bloom	0.114393	0.012314	-0.19845	0.17884
Veraison	-0.08155	0.011608	0.403747	0.129815
Constant	-2.32423	0.027668		
Inv.Mills ratio			-3.74038	1.872143
Year fixed effects		YES		
County fixed effects		YES		
N	212835		19504	

Table 5 Impact of PMI usage on pesticide use risk with grower random effects and p-values based on cluster robust standard errors in parentheses (NOTE: Models with '*Switchers only*' are estimated with only those growers who switched from not using to using the PMI during 1996-2007.)

	Aggregate Risk		**Surface Water Risk**		**Groundwater Risk**		**Soil Risk**		**Air Risk**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Received PMI	-2.06	-3.01	-1.58	-0.61	-4.02	-9.60*	0.24	-3.03	-1.92	-2.74
	(0.24)	(0.27)	(0.55)	(0.87)	(0.18)	(0.061)	(0.88)	(0.23)	(0.37)	(0.37)
Used PMI heavily or often	3.06*	5.18**	5.06*	4.69	3.21	4.71	2.50*	3.19*	2.65	5.35**
	(0.086)	(0.019)	(0.056)	(0.14)	(0.37)	(0.29)	(0.080)	(0.068)	(0.17)	(0.014)
1997	-2.45	-2.50	-4.88	-1.91	-5.64	-4.52	-0.74	3.16	-1.55	-3.38
1998	-0.71	0.83	-2.50	0.53	6.64	10.8	-1.23	0.34	-3.09	-2.70
1999	-6.91***	-8.68*	-20.3***	-21.1***	-8.43**	-12.7	-3.52	-3.76	-4.19	-6.54
2000	-6.72***	-11.6***	-12.5***	-15.9***	-14.6***	-22.5***	-2.97	-3.20	-5.00*	-10.1**
2001	-7.27***	-13.9***	-5.21	-11.8**	-14.6***	-23.1***	-2.50	-3.52	-8.76***	-15.6***
2002	-0.57	-4.19	-8.34**	-8.63*	14.0***	4.91	-4.72**	-1.84	-7.25**	-11.4***
2003	-4.01	-6.13*	-10.2**	-8.00	9.42**	3.13	-5.51**	-3.21	-9.61***	-12.5***
2004	0.20	1.00	-6.35	-4.54	21.3***	25.8***	-5.71**	-0.44	-9.99***	-11.8**
2005	-4.80*	-10.6***	-7.89*	-6.10	-4.44	-7.61	-4.44*	-1.74	-6.41**	-16.4***
2006	-3.00	-6.20	-4.39	-2.11	-0.45	-1.61	-4.76**	0.25	-5.83*	-11.7**
2007	-10.7***	-17.9***	-21.3***	-23.7***	-18.2***	-26.6***	-7.20***	-5.61*	-6.78**	-16.1***
Switchers only	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*
Grower RE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
County FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
R^2 Overall	0.21	0.43	0.39	0.51	0.39	0.47	0.13	0.29	0.18	0.44
R^2 Between	0.28	0.63	0.48	0.58	0.52	0.65	0.18	0.66	0.27	0.70
R^2 Within	0.094	0.23	0.15	0.26	0.28	0.35	0.038	0.069	0.053	0.12
N	546	250	546	250	546	250	546	250	546	250

* (**) [***] indicates statistical significance at 10% (5%) [1%] level