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Multi-Dimensional Responses to Risk Information: How do Winegrape Growers Respond to Disease Forecasts and to What Environmental Effect?

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ABSTRACT

How and how well growers manage the risks inherent in agriculture have 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. Better forecast information can benefit growers by improving their capacity to manage disease and pests effectively, but we must jointly consider multiple margins of adjustment in order to properly understand their response to this improved information. Using the case of California winegrape growers and high resolution panel data that includes plot-level treatments for powdery mildew, we characterize growers' response to a popular powdery mildew risk model that generates forecasts in the form of a daily risk index (PMI). Our analysis suggests that growers using the PMI adjust their powdery mildew management strategies along several margins of adjustment, including shifting from sulfur to more potent synthetic fungicides, increasing dosage rates, and using multiple products when the risk is high according to the PMI. The observed mix of these response adjustments varies by location and by output value. While field trials that only allow for treatment timing adjustments have suggested that the environmental benefits of the PMI could be substantially positive, our analysis of pesticide use risks to soil, surface water, groundwater, and air suggests that the net environmental impact of growers' multi-dimensional response to the PMI may actually be negative.

JEL Codes : D8, Q1, Q5

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MULTI-DIMENSIONAL RESPONSES TO RISK INFORMATION: HOW DO WINEGRAPE GROWERS RESPOND TO DISEASE FORECASTS & TO WHAT ENVIRONMENTAL EFFECT?

When grappling with uncertainty, we often crave more and better information in the hopes of improving future outcomes. This innate craving has long fueled attempts in many fields of human endeavor to forecast the future. In many such settings, how agents respond to new or better forecast information has direct implications for production, market and broader social outcomes. These links between uncertainty, information, responses, and outcomes are perhaps nowhere more clearly on display than in agriculture. How well or poorly producers manage the risks inherent in agriculture has direct welfare implications for producers and consumers both locally and beyond. Furthermore, producers' behavioral responses to these risks can have environmental implications and other spillover effects. In this paper, we test how wine grape growers in California alter their disease management strategies in response to improved disease forecast information and the environmental effects of these responses.

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, Herriges and Holtkamp 1992) or when pest outbreaks are unpredictable. Motivated by the latter justification for using pesticides as insurance, integrated pest management (IPM) aims to reduce pesticide use 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, processing and rapid dissemination 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 fact that producers can adjust their mitigation strategies along several dimensions simultaneously makes characterizing their response to new information as challenging as it is important.

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 necessitated by the explosive episodes of powdery mildew growth that are possible when optimal temperature and humidity conditions for the mildew 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.

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, Gubler and Leavitt 1994, Weber, Gubler and Derr 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. In addition to private benefits internalized by producers, the social and environmental benefits of reduced fungicide use due to better treatment timing could be substantial. Since powdery mildew affects several fruit crops in addition to grapes, many countries around the world could 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 technicians mechanically adjust the timing of powdery mildew treatments according to the PMI. How do growers with greater adjustment flexibility change their strategies in response to the PMI in practice? How do these potentially multi-dimensional responses affect net pesticide usage? In addressing these questions, this paper is the most rigorous assessment to date of how farmers use disease forecasting as a risk management tool, as well as the environmental impacts of its availability. 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.[2] Our empirical analysis sheds a broader light

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

[2] For a collection of these disease forecasting models see http://www.ipm.ucdavis.edu/DISEASE/DATABASE/diseasemodeldatabase.html (accessed 27 March 2012). In addition to these models, there other attempts to improve the information growers have at their disposal to target their disease and pest management strategies. For example, plant breeders are exploring the use of genetic engineering to enable plants to signal the presence of a pathogen via a fluorescent glow, which would allow

on how growers actually respond to forecasts derived from these models and the associated environmental impacts.

We estimate models of growers' disease management strategies using high resolution temporal and spatial data collected at the grower- and plot- level. The temporal and spatial resolution of this data allows us to estimate the impacts of receiving disease forecasts on farmer behavior at an unprecedented level of detail. We leverage the panel structure of our data to identify the impact of receiving the PMI on pesticide applications by comparing a grower's powdery mildew strategies before and after the grower started receiving the PMI. Building on recent work to estimate the plot-specific environmental risks associated with a given pesticide regime (Zhan and Zhang 2012), we test the impact of receiving the PMI on environmental risks using the same identification strategy. Because we do not have data on the efficacy of treatment regimens as influence by receipt the PMI, we cannot directly estimate the value of the PMI to producers. Understanding if and how growers use the PMI, however, is a first step in this direction.

Our results suggest growers do adjust their disease management strategies based on the PMI, but that this response is multi-dimensional, nonlinear and spatially heterogeneous. While some PMI recipients do tighten treatment intervals as the PMI increases as intended by its promoters, so do many non-recipients – presumably based on intuition and experience with powdery mildew. In comparison to this muted interval response relative to non-recipients, PMI recipients tend to more actively adjust other dimensions of powdery mildew treatment, including what product to use, whether to mix products in a single treatment and dosage rates. These complex responses are also distinctly nonlinear, with high PMI values inciting especially aggressive responses. PMI responses are dramatically different in different grape growing regions. Growers in the high value grape growing regions of the North Coast and Central Coast of California adjust treatment strategies most in response to the PMI. Since PMI recipients are not responding by adjusting intervals alone, the net environmental effect of the PMI is ambiguous and open to empirical testing. We use plot-level environmental risk scores (Zhan and Zhang 2012) to test this effect, which – counter to prevailing wisdom – suggests a negative

growers to treat only infected plants (see http://www.scidev.net/EN/NEWS/GLOWING-CROPS-COULD-MINIMISE-PESTICIDE-USE-1.HTML, accessed 27 March 2012).

environmental impact. Specifically, we find that PMI usage appears to offset about seven or eight years of general reductions in aggregate environmental risks.

1 BACKGROUND

The Economics of Pesticide Use

There is a rich literature in economics focused on pesticide use. Broad reviews of the theoretical and empirical issues addressed in this literature are available elsewhere (see Carlson and Wetzstein 1993, Fernandez-Cornejo, Jans and Smith 1998, Norgaard 1976). 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 overuse pesticides as a form of insurance that is effectively subsidized by the environmental costs that are not internalized by producers (Mumford and Norton 1984).[3] Based on this view, crop insurance can in principle reduce the use of pesticides by offering an insurance substitute (Carlson 1979, Feinerman, Herriges and Holtkamp 1992, Huang and Liu forthcoming), but evidence from the U.S. Midwest suggests that crop insurance may increase pesticide use in practice (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, Nijkamp and Vindigni 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. IPM includes decision rules based on economic thresholds (Fabre, Plantegenest and Yuen 2007) and better knowledge and information.

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

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[3] 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).

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, which can be shaped by both partial and general equilibrium effects (Lave 1963) and by the demand elasticity for the final product (Babcock 1990). The link between weather forecasts and risk is especially strong in the case of frost because frost events can be forecasted and can be devastating in the absence of any mitigation (Baquet, Halter and Conklin 1976). 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 environmental effects of changes in pest management decisions due to value of disease and pest forecasts (Moffitt, et al. 1986, Mumford and Norton 1984, Swinton and King 1994) and precision production technologies that enable more targeted practices (Khanna and Zilberman 1997). In contrast to this weather information and risk literature, we assess the impact of forecast information on producer responses – and do so at a higher resolution than previously possible using a unique dataset.

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 crop in California.[4] 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). For California's winegrape growers, powdery mildew control is arguably the most important single management practice: They spend more each year controlling powdery mildew and still suffer more losses to it than any other disease.

[4] Greenhouse and nursery products are the most valuable crop in California.

Damages due to powdery mildew often depend on the timing of first infection – making early season control critical.[5] 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.[6] Sulfur is also acceptable for use on organically certified wine grapes. As conditions change throughout the season, growers often switch to more potent synthetic fungicides such as quinoxfen, demethylation inhibitors (DMI) or strobilurin fungicides. Sulfur is, however, 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 and nonlinearly affected by climatic conditions.[7] 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. The PMI, based on the Gubler-Thomas model, aims to provide such a forecast using the documented relationship between temperature,

[5] 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. The susceptibility of various plant parts to powdery mildew infection changes during the season. To some extent, it affects most wine, raisin and table grape varieties, but some varieties are extremely susceptible to powdery mildew (e.g., Chardonnay, Cabernet Sauvignon, Chenin blanc) and others are less susceptible (e.g., Petite Sirah, Zinfandel, Semillon, and White Riesling).The epidemiology of powdery mildew on grapevines is explained in detail elsewhere (Pearson and Gadoury 1987, Sall and Wrysinski 1982, Ypema and Gubler 1997).

[6] Micronized sulfur is processed and formulated to provide better coverage on vegetation and to oxidize more slowly.

[7] 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.

humidity and ascospore release to predict initial disease onset (Gubler, et al. 1999, Thomas, Gubler and Leavitt 1994, Weber, Gubler and Derr 1996).[8]

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 risk).[9] Low index values of 0-30 indicate the pathogen is not reproducing. An index of 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– often via daily email messages. Increasingly, growers use their own on-site weather stations with integrated software to compute the PMI.

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

[8] The model and its forecast have been validated throughout the grape growing regions of California and other parts of the world. 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.

[9] 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 (e.g., after three consecutive days of six or more hours of optimal temperatures the PMI climbs to 60). 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 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.

million pounds in 2003 (8 percent) if only a quarter of raisin growers followed the PMI (UC Agriculture and Natural Resources 2005).[10]

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. Many in the industry assume that growers' baseline tendency is a calendar (or minimum interval) spray schedule. In this case, having more information on pest risk could only result in less frequent treatments. However, 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 hinge on PMI adoption among growers, especially those responsible for large shares of total fungicide applications.

2 MODEL

A few concepts from the literature on the economics of pesticide use are relevant to our analysis in this paper. Perhaps the most fundamental of such concepts is that 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). The role of uncertainty (e.g., Feder 1979) and the formulation and updating of expectations associated with the pest damage function have motivated Bayesian models 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 and product choice, for example, are key to most management strategies and are inherently dynamic. Rust (1987) develops a dynamic estimation model for a regenerative optimal stopping problem, where the state variable that ultimately affects outcomes is determined by a series of discrete investment decisions. In the same spirit,

[10] Wine grape growers manage powdery mildew even more aggressively than raisin growers and, based on this simple extrapolation, PMI use might generate even greater reductions in sulfur usage.

we develop a simple numerical optimal spraying simulation, but allow for discrete responses in two dimensions.

The first dimension of the treatment choice is how often to treat or, posed as the real-time decision facing the grower, "Based on the number of days since my last treatment, should I spray today?" At one extreme, which serves as a useful illustration in our model, a *naïve* grower locks in a treatment calendar at the beginning of the season and sticks with it throughout, regardless of daily changes to powdery mildew risk. While admittedly unrealistic, this is a common accusation leveled at growers. Alternatively, a grower who receives the PMI might set out with a calendar in mind and then constantly modify intervals according to this information. For this *informed* grower, treatment intervals are determined real-time as the result of daily binary choices of whether to spray or wait. 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 PMI information.

As a second margin of adjustment, there are several chemicals available for treating for powdery mildew, with different costs, protective strength, duration of protection, and environmental consequences. Farmers generally use either sulfur products, more potent synthetic fungicides such as quinoxfen, demethylation inhibitors (DMI) or strobilurin fungicides, or a combination thereof. 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. While in practice chemical choice can be constrained by state imposed minimum intervals (see Table 1) that disallow treating the same area with the same chemical before waiting a mandated number of days, our simulation imposes no such constraint.[11]

While the programming model we describe below only tests the first and second adjustment margins (when and what to spray, respectively), our empirical analysis allows for a third dimension: the dosage rate. 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,

[11] We also tested a model with a minimum interval constraint on chemical choice and it yielded the same general results, albeit with more complexity.

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.

Stochastic Optimal Spraying Model

For simplicity, we limit chemical choice to sulfur (*X*) and synthetic (*Y*) fungicides. Expected grape loss on plot *i* at day *t* is a function of the PMI, PMI_{it}, the interval since the last treatments of sulfur, I_{it}^{X}, and synthetic fungicide , I_{it}^{Y}. Spray intervals are determined by past chemical use up to the most recent treatments. Under the simplifying assumptions that the grower is risk-neutral, that monetary damages equal the market price of grapes grown, p_i , times the quantity lost, and that damages incurred do not affect the probability or magnitude of future damages, the grower solves the following optimization problem to minimize the sum of expected losses and chemical costs from the present day, t_0, to the end of the growing season:

$$\min_{X,Y} \sum_{t=t_0}^{T} p_i f(PMI_{it}, I_{it}^{X}(X_{it-1}, X_{it-2} \dots X_{i1}), I_{it}^{Y}(Y_{it-1}, Y_{it-2} \dots Y_{i1})) + \sum_{t=t_0}^{T} (p_X X_{it} + p_Y Y_{it}) \quad (1)$$

The problem in (1) can be solved analytically for a naïve grower, who sprays at regular and predetermined intervals. Because the informed grower’s problem involves a series of discrete choices that depend on continuously updated weather information it must be solved using stochastic mixed-integer programming.

One Dimensional Response: Interval Choice Only

We use numerical simulations to compare optimal spraying patterns for the *naïve* and *informed* growers, first with a one dimensional response and then with a two dimensional response. We make these comparisons for growers facing two different powdery mildew risk trajectories, and with two different types of grapes: low value and high value. We begin with the one dimensional problem, and assume a functional form for f_{it} , which is constant across farmers and time.

$$f(PMI_{it}, I_{it}^{X}) = (\alpha(PMI_{it}) - \sigma_X(\beta - I_{it}^{X})^{\gamma_X})^{\varphi} \quad (2)$$

The infection risk variable, PMI_{it}, is intentionally analogous to the PMI: it ranges from 0-10 and moves in a random walk, with $E[PMI_i]$ = 4.8 under the low PMI trajectory and $E[PMI_i]$ = 9.2 under the high PMI trajectory. The parameter σ_X is the protective strength of chemical *X*, γ_X is a duration of protection parameter between 0 and 1, φ is a parameter greater than 1 than ensures damage is increasing and convex in *PMI* minus protection, and β is some maximum number of periods after which the chemical has no protective power, i.e. $\beta - I_{it}^{X} \geq 0$.

We solve the model for a period of 5 days.[12] In the model growers do not face minimum interval constraints[13] and assume that the 5 day interval is preceded by a treatment of X. We solve the model for four growers – *naïve* low value, *informed* low value, *naïve* high value, and *informed* high value – each under conditions of a high PMI trajectory and a low PMI trajectory.

The simulation results are shown in Table 2 The *naïve* low value grower does not adjust her expectations for the PMI from day-to-day and solves (1) under a constant expectation of $E[PMI_i]$ = 7. The optimal strategy for this grower is to spray on days 2 and 4. The *informed* low value grower does not deviate from the *naive* calendar spray when the PMI is high. When the PMI is low, however, she only sprays on day 2. A similar pattern arises for high value growers. The *naïve* high value grower sprays every day. When the PMI is high, the *informed* high value grower also sprays daily. When the PMI is low, however, she only sprays on days 1 and 4, saving three sprays. That farmers should reduce sprays when they know the PMI is low is precisely the logic behind the inception of the PMI, but this response hinges on our assumption that growers only have one response (interval) at their disposal.

Two Dimensional Response: Interval & Chemical Choice

When a farmer has two chemicals of differing strengths and/or duration of coverage, the damage function in (1) becomes:

$$f(PMI_{it}, I_{it}^{X}) = (\alpha(PMI_{it}) - \sigma_X(\beta - I_{it}^{X})^{\gamma_X} - \sigma_Y(\beta - I_{it}^{Y})^{\gamma_Y})^{\varphi}, \qquad (3)$$

where $\sigma_X < \sigma_Y$, $0 < \gamma_X < \gamma_Y < 1$, and $\beta - I_{it}^{j} \geq 0$ for *j* = {*X*,*Y*}.[14] These assumptions imply that chemical *Y* is more potent, longer lasting, and more expensive than chemical *X*, as is the case

[12] In the model damage can occur on the 6th day, but growers will not spray on the 6th day because the problem does not continue afterward. In actuality, the period of powdery mildew risk spans much of spring and summer, but 5 days is sufficient to see patterns develop in the simulation. 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 to convergence when more days are added.

[13] This prevents the farmers from selecting spray patterns to circumvent minimum intervals rather than choosing what to spray based on chemical strength, duration, and price.

[14] The function in (3) assumes protection is additive. This assumption is not necessary to derive the key illustrative results presented in the paper. For instance, it is also possible to structure the damage function so that only the

when comparing synthetics to sulfur.[15] Here we present a set of simulation results for the *naïve* and *informed* growers with both low and high value grapes, allowing them to adjust chemical type in addition to treatment intervals.

As shown in Table 2, the low value, *naïve* grower sprays *X* on days 1 and 3 and *Y* on days 2 and 4. With high PMI the *informed* grower sprays exactly as does the *naïve* grower, but with low PMI she sprays only on day 2 with Y and day 4 with X. Receipt of the PMI has a slightly different effect on the treatment decisions of the high value grower. The *naïve* high value grower alternates treatments of X and Y for the entire five days. The *informed* high value grower forgoes the final treatment of X when the PMI is low. When the PMI is high, however, she switches the final spray from X to more potent Y.

In sum, once we allow for a two-dimensional response, use of the PMI can still lead to stretched intervals when the PMI trajectory is low, but it can also lead to increased use of the more potent treatments when the PMI is high (as it does for the high value grower). While the specific results are sensitive to parameter choice, this general key result is robust across a range of parameter values.[16] The model assumes growers are risk neutral, and allowing them to be risk-averse would likely magnify this result. In particular, introducing risk or loss aversion may introduce an asymmetry in the PMI response since growers are likely to respond more strongly to high risk than to 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

Our empirical analysis hinges on the high 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 wine-grape growers from 1996 to 2007 and includes spatially specific daily PMI forecasts for this period.

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protective power of the most recent chemical sprayed persists. We assume additive protection not only because it is simpler, but also because it is more realistic. We also abstract away from potentially important resistance complementarities: two chemicals can be jointly managed to slow resistance to either.

[15] We assume there are no synergistic effects between *X* and *Y*, although this assumption could be relaxed.

[16] The final parameter values were chosen because they allow the model to converge across all variations of the model.

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 use of the PMI. Members of the California Association of Winegrape Growers and several other state and local grape growers' associations were invited to participate in the survey. Despite favorable trials and widespread availability of high resolution PMI forecasts, roughly half of California grape growers actively use the PMI to control powdery mildew. However, adoption rates seem to be steadily increasing and are as high as 75% among wine grape growers in Napa and Sonoma counties where production value is high, varieties are highly susceptible to mildew, and the importance of locational branding can amplify growers' sensitivities to the environmental impacts of their production practices (Friedland 2002, Warner 2007) as well as their interest in local partnerships for promoting sustainable viticulture practices (Broome and Warner 2008). Nearly two-thirds of our surveyed growers have used or currently use the PMI to some degree (see Lybbert and Gubler 2008 for a preliminary analysis of the forecast adoption decision). In the present analysis, we include 67 growers from three major winegrape growing regions for which we had adequate PMI data (more below): North Coast (Napa, Sonoma, and Mendocino counties), Central Coast (San Luis Obispo county) and Central Valley (Fresno, Madera, and San Joaquin counties). Since there are important within region similarities and significant between region differences (e.g., in growing calendars, grape varieties, pest pressure, and production value), we disaggregate our analysis by these growing regions (Flaherty 1992).

Next, we obtained daily PMI values for locations near our surveyed growers.[17] 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 the plots of growers in our survey to the nearest station for which we have PMI data using linear distance measures. The mean distance from the plots included in our survey to their matched station is 13 km.

Our final data layer introduces an unprecedented daily resolution on pesticide management decisions. The data in this layer was collected as part of California's rigorous

[17] 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.

pesticide use reporting system administered by the Department of Pesticide Regulation (DPR). In this system, growers must obtain a pesticide use permit before applying any pesticides and then must file a pesticide use report (PUR) with their respective county agriculture commissioner each time they apply a pesticide. These PURs are collected across counties by the DPR and are publicly available via the DPR website at the plot level (see Epstein 2006 for more details about the PUR system). Each PUR contains the grower's 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 each of their plots. In our analysis, we use plot-level PURs to understand growers' powdery mildew treatment decisions. One aggregate analysis of PUR data and the potential impact of IPM on pesticide usage precedes our grower-specific analysis (Epstein and Bassein 2003).[18] 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 by year, which allows us to directly test the impact of the PMI on growers' powdery mildew strategies, pesticide usage, and environmental effect.

There are, however, a number of limitations with PUR data, two of which 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[19] and consultations with plant pathologists to identify powdery mildew treatments. 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 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[20]

[18] Several other inquiries – including both environmental and human health related – have used PUR data (e.g., Davidson 2004, Reynolds, et al. 2002).

[19] Available at http://www.ipm.ucdavis.edu/PMG/r302902111.html (accessed 10 March 2010).

[20] We reconstruct these treatment intervals as the number of days between consecutive powdery mildew treatments on a given plot. Often, growers treat over consecutive days (e.g., when plots are large and take more than one day to treat), in which case we used the day on which the highest proportion of the plot was treated as the center point of the treatment and compute the number of days between center points.

and thereby use plots as our unit of analysis, we are unable to control for unobservable plot characteristics over time (e.g., with plot fixed effects).

Table 3 contains an overview of the relevant dimensions of our data and highlights the stark differences in production value across the three regions. Our identification strategy (discussed in detail below) uses a battery of fixed effects associated with grower-plot-year combinations, of which we have 5,842 in our sample. In one of these specifications, we model the binary decision to spray for PM and take each day between the first and last PM treatment of the season as an observation. There are nearly a million of these grower-plot-days in our full sample, 45% of which are in the high value North Coast region. For the remaining specifications, we model product and dosage decisions conditional on having decided to spray for PM. This approach uses each PM treatment as an observation. In the full sample, we have a total of 23,958 treatments by growers not using the PMI and 28,224 by those using the PMI. Since our data begins as early as 1996, the year the PMI was first released, many of our growers switch from not using to using the PMI during our data window, which enables us to test the robustness of our results by estimating models for these 'switchers' only.

The empirical models that follow are based on treatment differences between those who receive the PMI in a given year with those who do not. The simple descriptive statistics in table 4 offer an unconditional comparison of the interval and fungicide use tendencies of the growers in our sample. 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 receiving counterparts after spraying synthetic products. In addition to not controlling for any of the factors other than receiving the PMI that potentially affect PM treatments, these unconditional comparisons pool together growers from all three regions, which likely respond to the PMI in quite distinct ways. To exploit complementary strengths, growers often mix sulfur and synthetic products to create cocktail treatments. These cocktail treatments are not reflected in this table but are analyzed below.

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 response to the PMI. Since reducing the environmental impact of pest management practices is fundamental to disease forecast models as a component of IPM, understanding this impact empirically is critical – but also complicated once we allow for simultaneous adjustment on more than one margin. PMI users may 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 to increases in the index, while being relatively unresponsive to a low PMI.

In our pursuit of these two empirical objectives, we leverage the panel structure of our data and control for unobservable determinants of PM management with plot-year and year fixed effects. In addition to comparing the treatment tendencies of growers using the PMI to those not using the PMI, we also estimate response models for growers who initially did not use it but switched to using the PMI during the coverage of our data. Where we have enough 'switchers'(North and Central Coast regions), growers serve as their own counterfactual in a before-after identification approach with grower fixed effects to control for time invariant unobservables that may be correlated with PMI usage. Our results are largely robust to this before-after test with grower fixed effects.

Two econometric issues of potential concern are worth mentioning. First, our identification strategy compares the pesticide use strategies of non-recipients to PMI recipients, except for specifications that include only switchers. This raises potential concerns of endogeneity bias since PMI receipt is sometimes a choice variable itself. We note, however, that many growers received the PMI as an added feature to an existing agro-services subscription or an upgraded onsite weather station. While the data contain both receipt and use of the PMI, we use PMI receipt as the explanatory variable of interest to limit the potential for endogenity bias. Second, the various response variables we include in the models below may be jointly determined. For example, anecdotal evidence suggests that these joint responses may be recursive, with the grower first deciding when to treat, then choosing a treatment product and dosage rate. Although we have experimented with a system of equations estimation approach, we remain concerned about the strong assumptions required to identify the system. We therefore opt for an equation-by-equation estimation approach that should yield consistent estimates albeit with some potential loss of efficiency.

A. How do growers respond to the PMI?

We characterize growers' response to the PMI along three margins of adjustment: (1) when to spray, (2) what to spray, and (3) how much to spray. PM treatment is conditioned on several factors in addition to expected disease pressure, including the growth phase of the vines. Furthermore, the evolution of PM pressure varies widely by year and across space, with PM outbreaks often flaring up at the plot level according to vagaries in the micro-climate and to the susceptibility of different grape varieties. We use a variety of control variables and plot-year fixed effects to account for these factors. Conditional on these determinants of PM treatment, we aim to compare growers who receive and use the PMI with those who do not. While growers' PMI response may be nonlinear in important ways, we begin with simple approximations that assume that their response is piecewise linear. With these broad tendencies in mind, we then estimate more flexible specifications that accommodate nonlinearities in growers' PMI response. Since grape growing regions in California have distinct agroclimatic conditions, we estimate these specifications separately for each growing region.

We use variations of two similar specifications as the basis for modeling of growers' responses. In the first, we pool PMI recipients and non-recipients together and use interaction terms to test for PMI recipients' response to the PMI. In the second specification, we estimate separate response functions for recipients and non-recipients. The first (pooled) specification allows for a continuous spline response to the PMI and is of following form:

$$\begin{aligned} R_{ijdt} = \alpha_0 + \beta_0 PMI_{ijdt} + \beta_1^L \left(Z_{it} \times PMI_{ijdt} \middle| L \right) + \beta_1^M \left(Z_{it} \times PMI_{ijdt} \middle| M \right) + \beta_1^H \left(Z_{it} \times PMI_{ijdt} \middle| H \right) \\ + \beta_2^{\text{Pre}} \left(Z_{it}^{\text{Pre}} \times PMI_{ijdt} \right) + \beta_2^{\text{Post}} \left(Z_{it}^{\text{Post}} \times PMI_{ijdt} \right) + \mathbf{x_{ijdt}}'\boldsymbol{\varphi} + \boldsymbol{\lambda}_{\mathbf{ijd}} + \boldsymbol{\mu}_{\mathbf{ijt}} + \varepsilon_{ijdt} \end{aligned} \quad (4)$$

where R_{ijdt} is a response variable that captures one of the three adjustment margins for grower *i* on plot *j* on day *d* in year *t*, PMI_{ijdt} is the relevant PMI value associated with that point in time and space,[21] $Z_{it} = \{0,1\}$ indicates whether or not grower *i* received the PMI in year *t*, and $PMI_{ijdt} \middle| s$ is the relevant PMI conditional on it being in range *s*, where *s* is explicitly stated in the

[21] Since growers typically receive the PMI at the end of the day on which it is calculated or the next day, we assume that the relevant PMI value for our response models is lagged one day. In other words, we assume that growers adjust today's PM treatment based on yesterday's PMI. To simplify notation, we use PMI_{ijdt} to indicate the PMI value lagged one day rather than $PMI_{ij,d-1,t}$.

construction of the PMI as low (0-30), moderate (30-60), or high (60-100).[22] We model this linear spline response function assuming continuity at the transition between ranges. The vector of parameters $\boldsymbol{\beta}_1$ is of primary interest and indicates how PMI recipients respond to the PMI when compared to non-recipients, whose baseline responsiveness to disease pressure is captured by β_0. When *R* indicates growers' powdery mildew treatment interval, $0 > \beta_1^L > \beta_1^M > \beta_1^H$ implies that PMI recipients tighten intervals as the PMI increases – or, alternatively, stretch intervals as the PMI decreases – and do so more aggressively as the PMI goes from low to moderate to high. Note that in this specification we use the PMI as a proxy for growers' baseline intuition about PM risks (e.g., based on the common pre-PMI advice, "if you like the weather, then so does PM."). While a simpler proxy for this intuition, such as average daily temperature, might be sufficient, using the PMI to proxy for baseline intuition makes this a strong test for recipients' response to the PMI.[23]

To get unbiased estimates of the parameters of interest in (4), we include several control variables, where $Z_{it}^{\text{Pre}} = \{0,1\}$ indicates that grower *i* in year *t* would eventually have access to the PMI and $Z_{it}^{\text{Post}} = \{0,1\}$ indicates that the grower had stopped using PMI in year *t*. Thus, the vector $\boldsymbol{\beta}_2$ controls for pre-receipt PMI response differences between recipients and non-recipients and between the few growers who stop receiving the PMI and other growers. Lastly, $\mathbf{x}_{\mathbf{ijdt}}$ are prior treatment variables that control for features of the preceding powdery mildew treatment, $\boldsymbol{\lambda}_{\mathbf{ijd}}$ are growth phase fixed effects,[24] $\boldsymbol{\mu}_{\mathbf{ijt}}$ are grower-plot-year fixed effects to control for unobservables associated with microclimatic variation across plot-years, and ε_{ijdt} is an error term.

While the piecewise linear response functions above offer easy parametric tests of growers' response to the PMI, a more flexible specification that allows for nonlinear differences between recipients and non-recipients is equally useful. For this second type of specification, we

[22] Treatment guidelines are typically given for these three categories of risk, as opposed to for each 10 point interval on the PMI.
[23] As a simpler proxy for baseline intuition, we have used the two day change in PMI, which effectively strips the 'memory' out of the PMI model. The results are qualitatively robust to this simpler proxy and, if anything, statistically stronger.
[24] These fixed effects control for the five growth phases – bud break, shoot growth, bloom, and veraison. The timing of these growth phases is assumed constant across years, but varies across growing region (see Flaherty 1992)

model PMI responsiveness separately for recipients and non-recipients using the cubic function:[25]

$$\begin{aligned} R_{ijdt} &= \alpha_0^Z + \beta_{11}^Z PMI_{ijdt} + \beta_{12}^Z PMI_{ijdt}^2 + \beta_{13}^Z PMI_{ijdt}^3 \\ &\quad + \beta_{21}^{\text{Pre}}\left(Z_{it}^{\text{Pre}} \times PMI_{ijdt}\right) + \beta_{22}^{\text{Pre}}\left(Z_{it}^{\text{Pre}} \times PMI_{ijdt}^2\right) + \beta_{23}^{\text{Pre}}\left(Z_{it}^{\text{Pre}} \times PMI_{ijdt}^3\right) \\ &\quad + \mathbf{x_{ijdt}}'\boldsymbol{\varphi}^{\mathbf{Z}} + \boldsymbol{\lambda}_{\mathbf{ijd}}^{\mathbf{Z}} + \boldsymbol{\mu}_{\mathbf{ijt}}^{\mathbf{Z}} + \upsilon_{ijdt}^Z, \end{aligned} \tag{5}$$

where Z again indicates receipt of the PMI. In contrast to (4), this cubic specification uses a polynomial to fit nonlinearities in growers' response to the PMI. Since we estimate(5) separately for recipients and non-recipients, the other coefficients can differ for these two subsets of growers as well. Rather than displaying the estimated coefficients this specification, we depict the results graphically by computing a conditional response function across PMI values that conditions out the effect of the control variables and fixed effects on PM treatment response (Figures 1-4).

Identification Strategy. The specifications above use comparisons between PMI recipients and non-recipients to understand how growers adjust treatment strategies in response to disease forecasts. Standard concerns emerge if PMI receipt is endogenous. Although some growers actively sought out the PMI as it became available, many simply started receiving the forecast as part of a standard package of daily weather information – either from their own weather station or from a service provider. As mentioned previously, PMI receipt is therefore less problematic than PMI use, and we use PMI receipt throughout to distinguish PMI from non-PMI growers. Still, we acknowledge that recipients may differ from their non-recipient counterparts in systematic but unobservable ways. For our purposes, average differences in disease treatment tendencies (e.g., average treatment intervals, average dosage rates, etc.) are less worrisome than systematic differences between non-recipients' and recipients' responsiveness to their perceptions of disease risk (where recipients' are informed by the PMI). Although nuanced, we recognize this as a potential concern and formulate an identification strategy accordingly. In the absence of valid instruments, IV estimates may well be worse than any bias introduced by the quasi-endogeneity of PMI receipt, so we seek to improve our identification in three other ways.

[25] Since the results are robust to controlling for Z_{it}^{Post} (as in equation (4)) we opt for a simpler specification.

First, in both specifications above we include plot-year fixed effects $\boldsymbol{\mu}_{ijt}$. Thus, the PMI response parameters are estimated within plot-year combinations, implying that systematic differences between growers and plots in the baseline probability of spraying, chemical sprayed, and dosage are not the basis for estimating PMI responsiveness. Second, we include pre-receipt PMI responsiveness in both specifications. This enables us to test for pre-existing response differences between growers who ultimately get the PMI and those who do not. Even if this test reveals response differences, including these pre-receipt responsiveness parameters nets these differences out of the PMI response parameters. As a third identification tack, we estimate the above specifications including only growers who switch from non-recipient to PMI recipient during our window of analysis. Results from these 'switchers only' estimations continue to include plot-year fixed effects, implying that these within estimates compare recipients to their pre-receipt selves. While these switcher only results provide a strong test of growers' response to the PMI, note that we have many observations for switchers in the North Coast region, but fewer in the Central Coast and Valley regions.

<u>A1. When to spray?</u> To estimate these specifications for the first response dimension – when to spray – we use two related response variables: (i) whether or not to spray on a given day {0,1} and (ii) the interval since the last PM treatment. For (i), we estimate a linear probability model using data at the grower-plot-day level, which is the highest temporal resolution our data allows (see Table 3). We use the PM disease window, which varies by growing region, to determine which days are potential PM treatment days (Flaherty 1992).[26] For (ii), we include only PM treatment days (see number of PM treatments in Table 4). As additional controls, $\mathbf{x}_{ijdt}$, we construct two types of variables to reflect the most recent prior PM treatment. First, we include a dummy variable indicating whether the last PM treatment included multiple products (i.e., 'cocktail' treatment). Second, we construct measures to reflect the dosage rate used in the last treatment. To accommodate the wide range of dosage rates and units of measurement across products, we compute the percentile of the dosage rate for each product and each region separately. Where multiple products are used we combine these dosage percentiles into a weighted average for the treatment weighted by the share of the plot treated.

[26] Adjusting this PM window at the grower-plot level is possible by excluding the first and last PM treatment of the season for each plot and only including the days between these first and last treatments.

Table 5 contains the pooled spline regression results estimated and shown separately for the three growing regions. Each column in this table represents a different response dimension. Throughout, we calibrate the range of the PMI from 0 to 1 so the point estimates reflect the response change induced by a change in the PMI from 0 (no risk) to 1 (maximum risk). In the first two columns of Table 5, the coefficient on PMI suggests that non-recipients tend to respond to perceived higher PM risk by increasing the probability of spraying and tightening intervals – at least in the North Coast and Valley regions – but the magnitude of this response is quite small: the probability that non-recipients spray for PM increases by less than 2% when the PMI increases from 0 to 100. This limited – but statistically precise – baseline response is offset by the response of PMI recipients, who are actually *less* likely to spray for PM and more likely to stretch intervals as the PMI increases. While this runs counter to a uni-dimensional response model, remember that in practice growers have other margins of adjustment. As discussed shortly, this response is likely due to more aggressive responses along these other margins of adjustment, which may necessitate this counterintuitive timing response because of differences in minimum intervals between chemical types. In the first two columns, the pre-receipt coefficients are statistically zero, suggesting that there are no systematic responsiveness differences between recipients pre-receipt and non-recipients. Results for switchers only (Table 6) imply similar timing responses to the PMI, suggesting that these patterns are not due to unobservable differences between recipients and non-recipients.

The conditional probability functions depicted in Figures 1 and 2 are based on the cubic response function in specification (5). These graphical results allow for direct comparison of the response function for PMI recipients and non-recipients. In contrast to testing the interaction coefficients in the linear or spline regression, which captures the relative responses of PMI recipients, these conditional response functions depict growers' absolute response to the PMI. These functions suggest that growers' timing response to the PMI is nonlinear with dramatic differences across the three regions. Overall the slope of the interval response function in Figure 2 is negative for both recipients and non-recipients – suggesting a general tendency to tighten intervals as the PMI increases – and often appears to be more non-linear – perhaps due to the explicit recommendation ranges of the PMI.

A2. What to spray? We consider growers' product choice as the next response variable in the specifications above. Sulfur products are growers' default PM treatment and are relatively inexpensive, but synthetic fungicides can offer greater protection. Although growers can also opt for biological (e.g., Serenade) and contact treatments (e.g., JMS Stylet Oil), over 90% of PM treatments consist of sulfur or synthetic fungicides. In our analysis of this response dimension, we therefore focus exclusively on sulfur and synthetic products and estimate linear probability models of growers' choices between these two types of products.

The 'Product choice' columns in Tables 5 and 6 display the spline estimates for the linear probability model of sulfur and synthetic treatments. These estimates provide some evidence of shifting from sulfur to synthetic treatments as a PMI response, particularly in the higher value North Coast and Central Coast regions. While these patterns are less apparent with switchers only in Table 7, the conditional response functions in Figures 3a and 3b provide more compelling evidence of this tendency – even when focusing on switchers only.[27]

A3. How much to spray? As the third dimension of PMI response, we consider growers' decision of how much to spray. We capture this with two different variables: dosage percentiles and cocktails consisting of multiple products. Note that because product labels often provide a range of recommended dosage rates, growers have the flexibility to adjust their dosage rates within this range (but cannot exceed the maximum dosage rate listed on the label). As explained above, we compute dosage percentiles across all the treatments in our data by product and by region. Where multiple products are used in a single treatment, we compute a weighted average percentile using percent of the plot treated for each product as the weight.

Dosage response results in Tables 5 and 6 provide some evidence that PMI recipients increase dosage rates with the PMI, but there is little uniformity in this response across regions. We also note that there appear to be pre-receipt differences in growers' dosage response. The cubic response functions in Figures 4a and 4b indicate that North Coast recipients apply synthetics at higher relative dosage rates than non-recipients and that this difference gradually widens as the PMI increases. Central Coast growers continue to demonstrate a non-linear response that seems to reflect the low, moderate and high PMI ranges contained in

[27] A comparison of synthetic use among recipients versus non-recipients is only possible for switchers is the Napa-Sonoma region. There is not a large enough sample size of PM treatments for switchers in the other countries.

recommendations. The spline results in Tables 5 and 6 suggest a few weak patterns in growers' cocktail response to the PMI. In the North Coast region, recipients are more likely to use cocktails than non-recipients, but while this relative difference widens as the PMI increases there does not appear to be an absolute response in the probability of combing multiple products as the PMI increases.

Table 7 summarizes the differences between PMI recipients and non-recipients in both levels and relative PMI responsiveness. Interestingly, the level differences persist in the North and Central regions even when we restrict our focus to switchers, implying that these differences may not be entirely due to grower self-selection into PMI receipt. Most of the response differences indicate that PMI recipients opt for more aggressive treatment strategies as the PMI increases. While growers appear to become less aggressive as the PMI increases in a few cases (e.g., stretching intervals in the Central Coast region), this is likely an indirect, secondary response to a more aggressive primary response (e.g., shifting to synthetics). This summary of results highlights the fact that interval adjustment is but one response dimension and a minor one at that. In contrast to early projections for the PMI that considered only the interval response and assumed minimum interval treatments as the baseline, the environmental effects of this complex multidimensional response are ambiguous and therefore an open empirical question.

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

Our analysis allows for growers to respond to the PMI by adjusting when, what and how much to spray for PM. We find evidence that growers' response to the PMI involves adjustments along all three dimensions and some shifting between dimensions as the PMI passes from low to moderate to high values. This multidimensional and nonlinear response makes the environmental impact of PMI receipt difficult to assess. The simple simulation model above and initial projections about the potential environmental impact of the PMI – both of which predict a positive environmental impact if growers can only respond by changing treatment intervals – show how unambiguous predictions of positive environmental impacts may be misleading because they ignore other possible response dimensions. In this section, we test the net environmental impact of PMI usage knowing that growers' response is both multidimensional and nonlinear.

To do this we use the Pesticide Use Risk Evaluation (PURE) model, which 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 (Zhan and Zhang 2012). 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.

We have annual PURE risk scores for 84 of our surveyed growers.[28] The full PURE model evaluates the pesticide risks associated with all the pesticides applied on a given plot and registered with pesticide use reports. These plot-level annual risk scores can then be aggregated to an individual grower based on the grower's ID. In addition to these full PURE risk scores, we use risk scores based on a restricted PURE model that only includes PM treatments. That is, we exclude all non-PM treatments before running the PURE model to generate risk scores. We report results for risk scores based on the full and restricted PURE model. Although more pesticide applications target PM than any other disease or pest, there are likely to be differences between these sets of risk scores, with pros and cons to each in our application. Because the time step in this PURE analysis is annual instead of daily as above, we do not merge these data with daily PMI data and are not constrained by the spatial coverage of our PMI data (as we are in the response analysis above). Finally, note that several of the environmental factors included in these scores lie outside growers' control and the analyst's view, which potentially dilutes the relationship between the PMI receipt and risk scores and thereby strengthens the test for a difference.

Table 8 shows that PMI recipients have uniformly higher mean risk scores and the difference in these means is statistically significant for groundwater and soil risk scores. When only PM treatments are included, the scores are significantly higher for PMI recipients for all but air risk. Virtually the same results emerge when we include only growers who switch from not receiving to receiving the PMI to mitigate concerns over selection. These simple mean comparisons are suggestive, but do not control for annual and regional variation in PM treatment

[28] Note that we are able to include several surveyed growers who are not included in the response analysis above due to PMI data limitations. In the case of this PURE analysis, we do not use PMI data and are therefore not constrained by PMI limitations.

strategies. To assess the impact of receiving and using the PMI on these risk scores more carefully, we estimate the following model

$$Risk^{x}_{ijt} = \beta_0 + \beta_1 Z_{it} + \beta_2 Z^{\text{Pre}}_{it} + \gamma_t + \mu_j + (\upsilon_i + \varepsilon_{ijt}) \quad (6)$$

where x ={aggregate, surface water, groundwater, soil, air}, Z is (again) a dummy variable indicating whether grower i received the PMI in year t, Z^{Pre}_{it} is (again) a pre-receipt dummy, γ_t is a year fixed effect,[29] μ_j is a county fixed effect, and υ_i is a grower random effect.

Table 9 contains the estimation results from this specification for all growers, which includes growers outside our four growing regions that are excluded from the analysis of treatment response for lack of daily weather data.[30] Taking the coefficients on PMI receipt, these results suggest that growers change their PM management strategies in response to the PMI in a way that increases aggregate risks to the environment. This negative net environmental impact is evident when we include switchers only, which implies that this result is robust to controlling for unobservable differences at the grower level. As further confidence of a causal interpretation of these results, the coefficient on pre-PMI receipt is statistically zero at the 10% level across these models. Since an absolute interpretation of these risk score changes is complicated by the construction of the PURE model, a relative interpretation must suffice. Due to general recent improvements in pesticide management, the aggregate risk score of our growers falls by about 0.75 each year (based on a time trend included in the model). Thus, PMI usage appears to offset about seven or eight years of general reductions in aggregate environmental risks.

As a final test of this environmental impact, we use our subset of growers who switch from non-recipient to PMI recipient and formulate an event study approach. Specifically, we estimate switchers' risk score relative to their first year of receipt while controlling for a linear time trend and county fixed effects. We display these results graphically in Figure 5. Environmental risks increase in association with receipt of the PMI and these effects are often statistically significant.

5 CONCLUSIONS

[29] Alternatively, we include a trend variable, which imposes a linear year effect but does not change the coefficients on PMI.

[30] These results are robust to disaggregation by region. These region-specific results suggest that the increase in risk is typically larger in the high value North Coast region than in the other two regions.

Uncertainty fuels our innate craving for more and better information in the hopes of improving future outcomes. In many settings, how agents respond to new or better forecast information has direct implications for market and broader social outcomes. In agriculture, 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. Better forecast information can certainly benefit growers and improve their capacity to manage disease and pests effectively, but we must jointly consider the various dimensions of adjustment available to growers in order to properly understand their response to this improved information, and the environmental consequences of adjustment.

Using the case of California winegrape 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 forecasts in the form of a daily risk index (PMI). While we find some evidence of the assumed interval response, our analysis suggests that growers using the PMI primarily adjust their product choice and dosage rates in response to the PMI when the risk is high. While this core empirical result is robust across a variety of specifications, 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 environmental risk results suggest that the net environmental impact of this documented multi-dimensional response to the PMI may actually be negative, particularly in high-value production areas. Our point estimates suggest that the increase in environmental risks associated with using the PMI roughly offsets the *decrease* in risks associated with seven to eight years of improvements in pest management practices.

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.

We conclude with a final and intriguing conjecture. The negative net environmental impact of improved disease forecasts we find may be due in part to a double 'risk response asymmetry': first, in the risk responses of model builders and, second, in the risk responses of growers. In the calibration of forecasting models, model builders rationally fear false negative predictions more than false positive predictions. This rational response emerges because false negatives can bring dire consequences when the underlying stochastic process is characterized by nonlinearities that can lead to explosive risk episodes, while false positives have more mundane effects and modest costs. Moreover, a basic observability problem pushes model builders to choose conservative calibration of their forecast models: false negatives are readily observable by PMI users but false positives are not. The second asymmetric risk response occurs with growers, who appear to respond aggressively when the PMI is high, but may continue with business as usual when it is low. As long as growers and modelers do not take into account each other's asymmetric risk response, these have the effect of magnifying the overall risk response relative to what it would be under risk neutrality. At a time when increasingly sophisticated forecasts are flourishing in many fields – often with the intent of improving market and societal outcomes – this double asymmetry merits attention from economists and psychologists alike.

1

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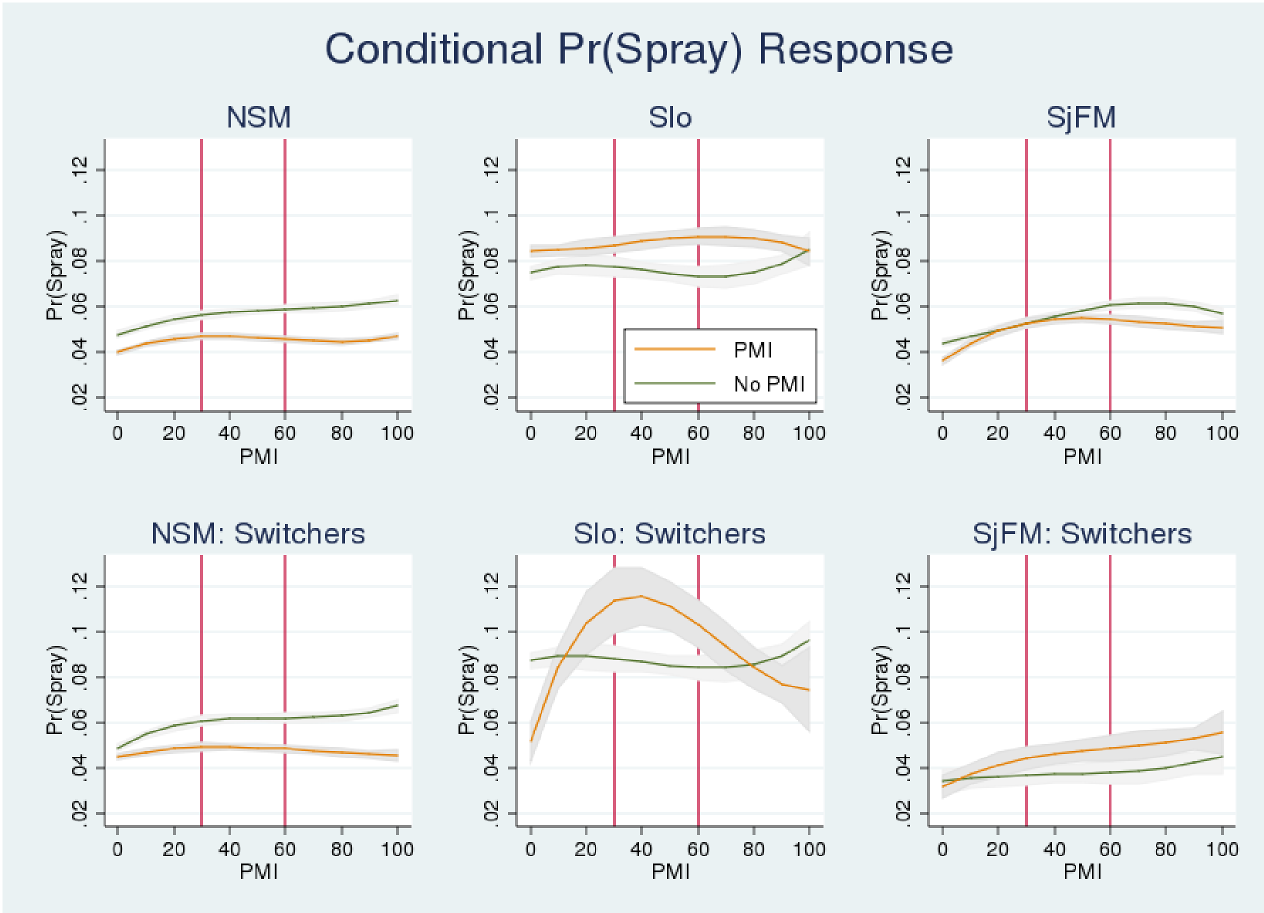

Figure 1 The conditional spray decision as a function of PMI with 90% confidence intervals (based on cubic response specification). NSM=North Coast (Napa, Sonoma, Mendocino), Slo=Central Coast (San Luis Obispo), SjFM=Valley (San Joaquin, Fresno, Madera). Orange line with darker confidence band represents PMI recipients.

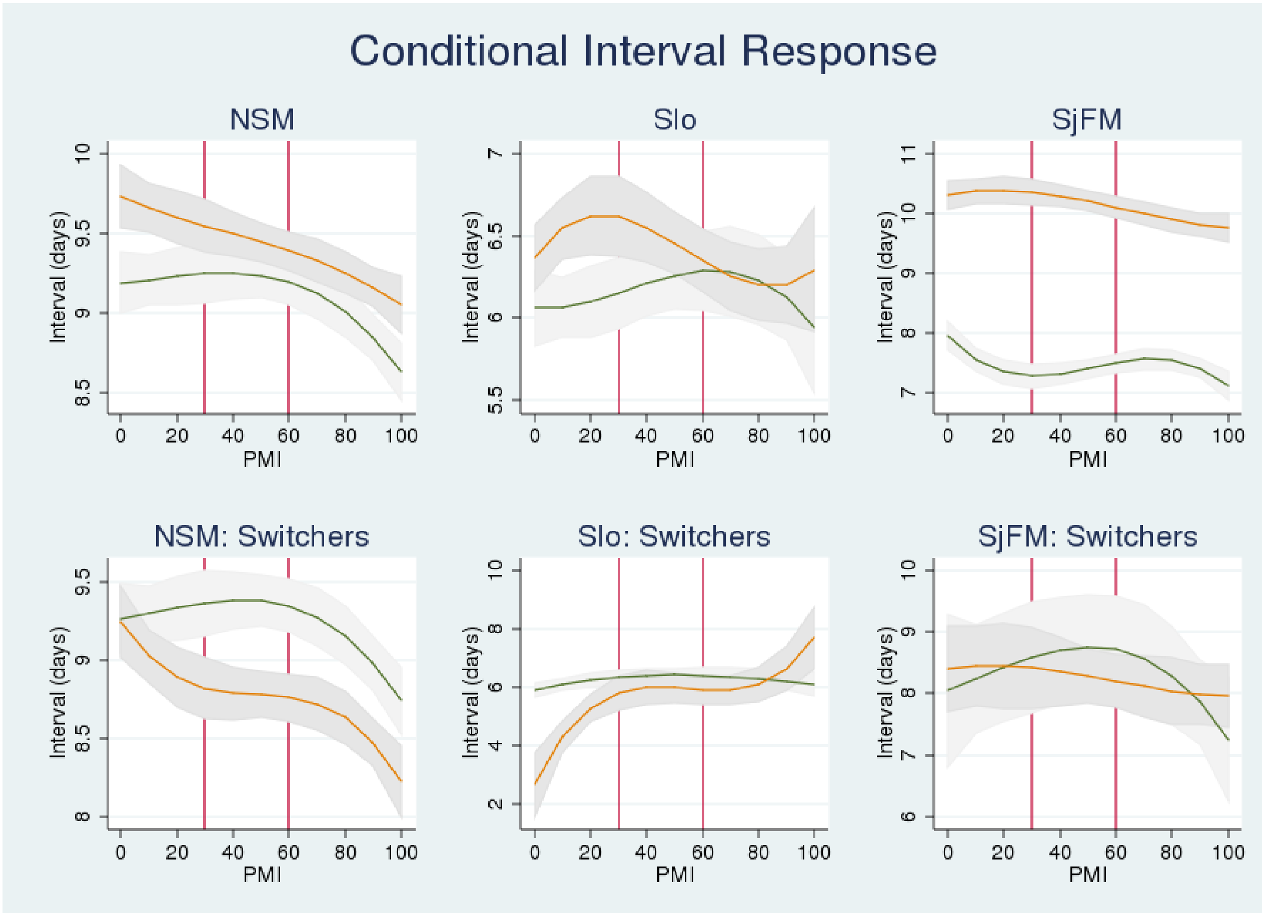

Figure 2 The conditional interval decision as a function of PMI with 90% confidence intervals (based on cubic response specification). Top panel includes all growers. Bottom includes only growers who switch from not receiving to receiving the PMI. Orange line with darker confidence band represents PMI recipients.

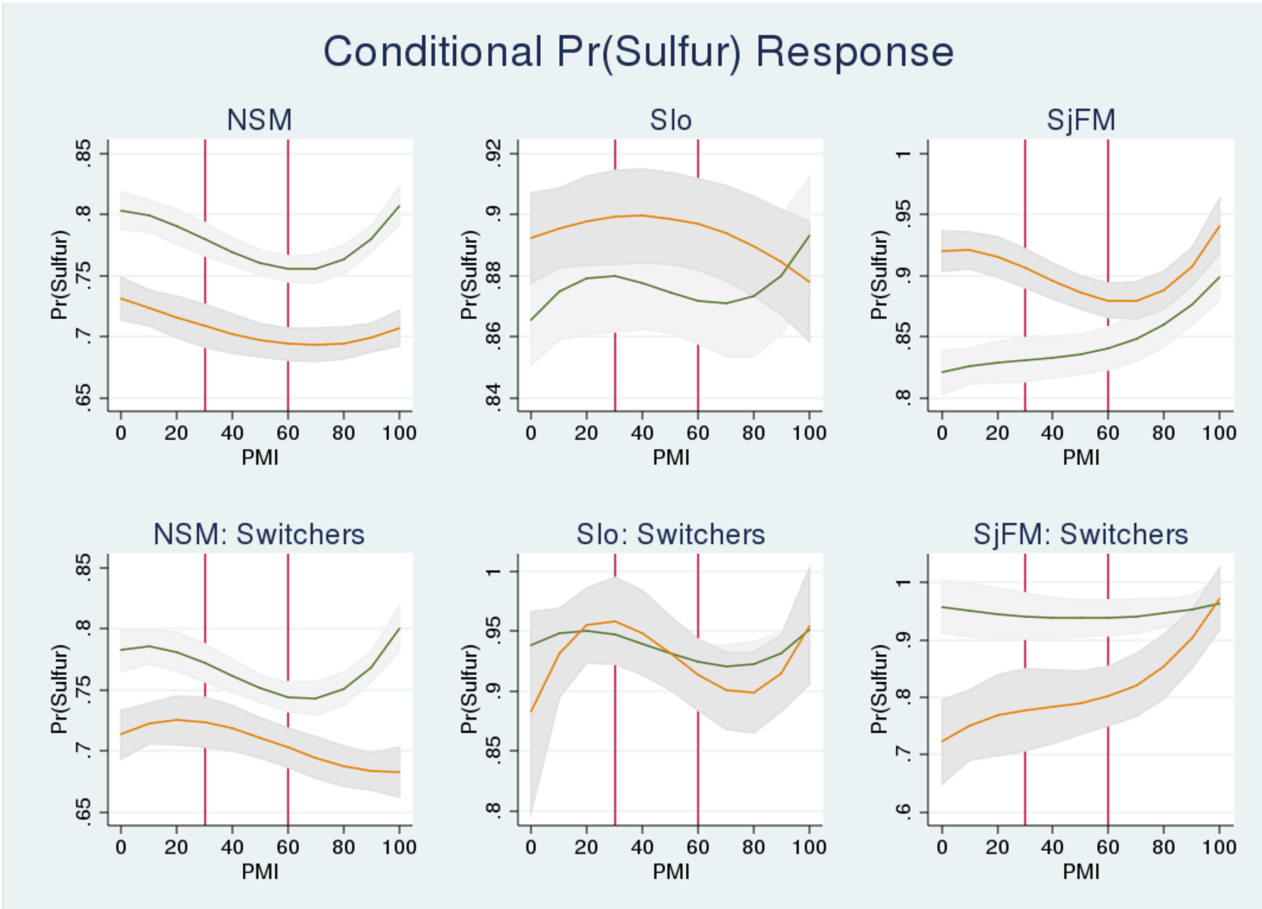

Figure 3a The conditional linear probability of spraying sulfur as a function of PMI with 90% confidence intervals (based on cubic response specification). Top panel includes all growers. Bottom includes only growers who switch from not receiving to receiving the PMI. Orange line with darker confidence band represents PMI recipients.

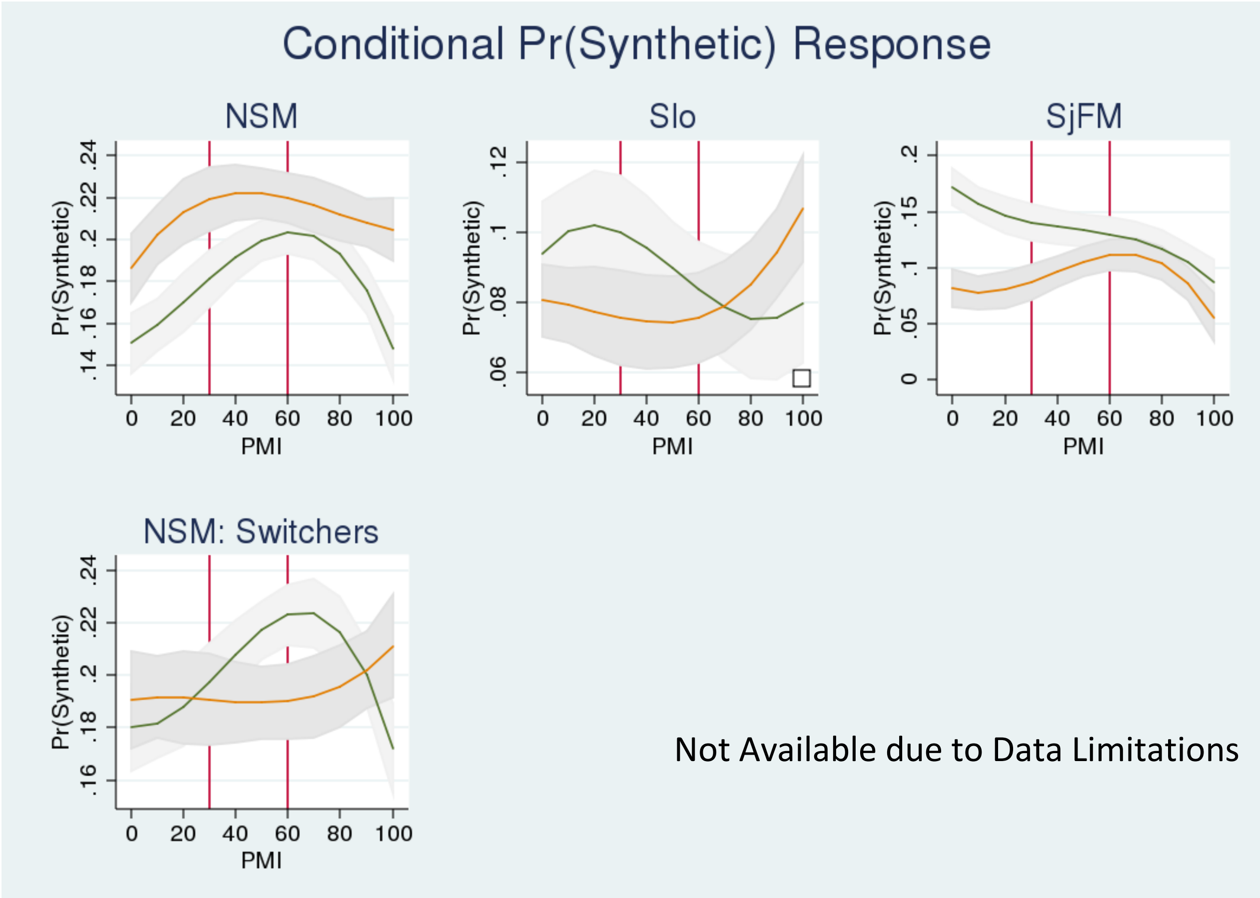

Figure 3b The conditional linear probability of spraying synthetic fungicides as a function of PMI with 90% confidence intervals (based on cubic response specification). Orange line with darker confidence band represents PMI recipients.

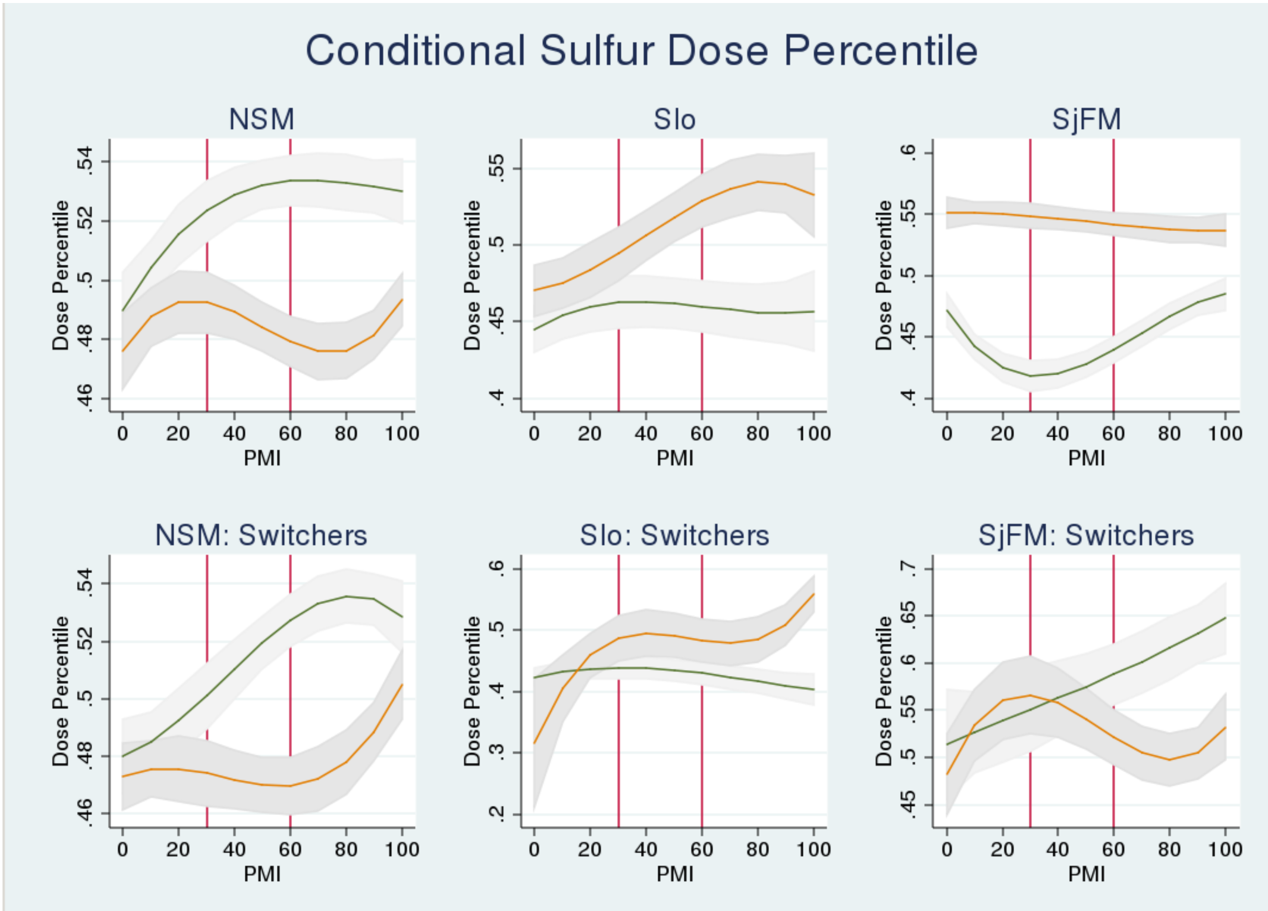

Figure 4a The conditional relative dosage response for sulfur as a function of PMI with 90% confidence intervals (based on cubic response specification). Relative dosage based on dosage percentile by product. Top panel includes all growers. Bottom includes only growers who switch from not receiving to receiving the PMI. Orange line with darker confidence band represents PMI recipients.

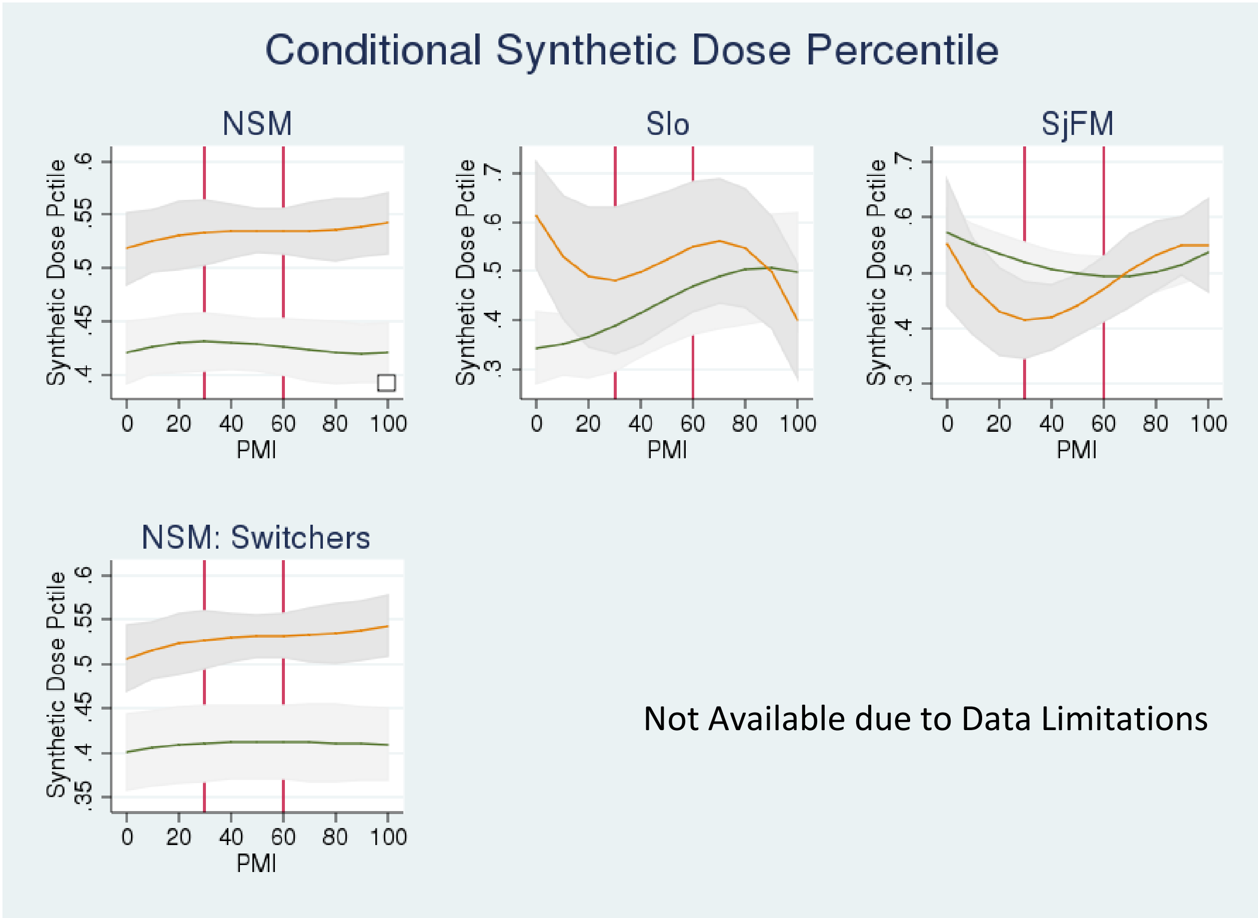

Figure 4b The conditional dosage percentiles for synthetic fungicides as a function of PMI with 90% confidence intervals (based on cubic response specification). Dosage percentiles measure relative dosage and are computed separately for each product, including all PM treatments. Orange line with darker confidence band represents PMI recipients.

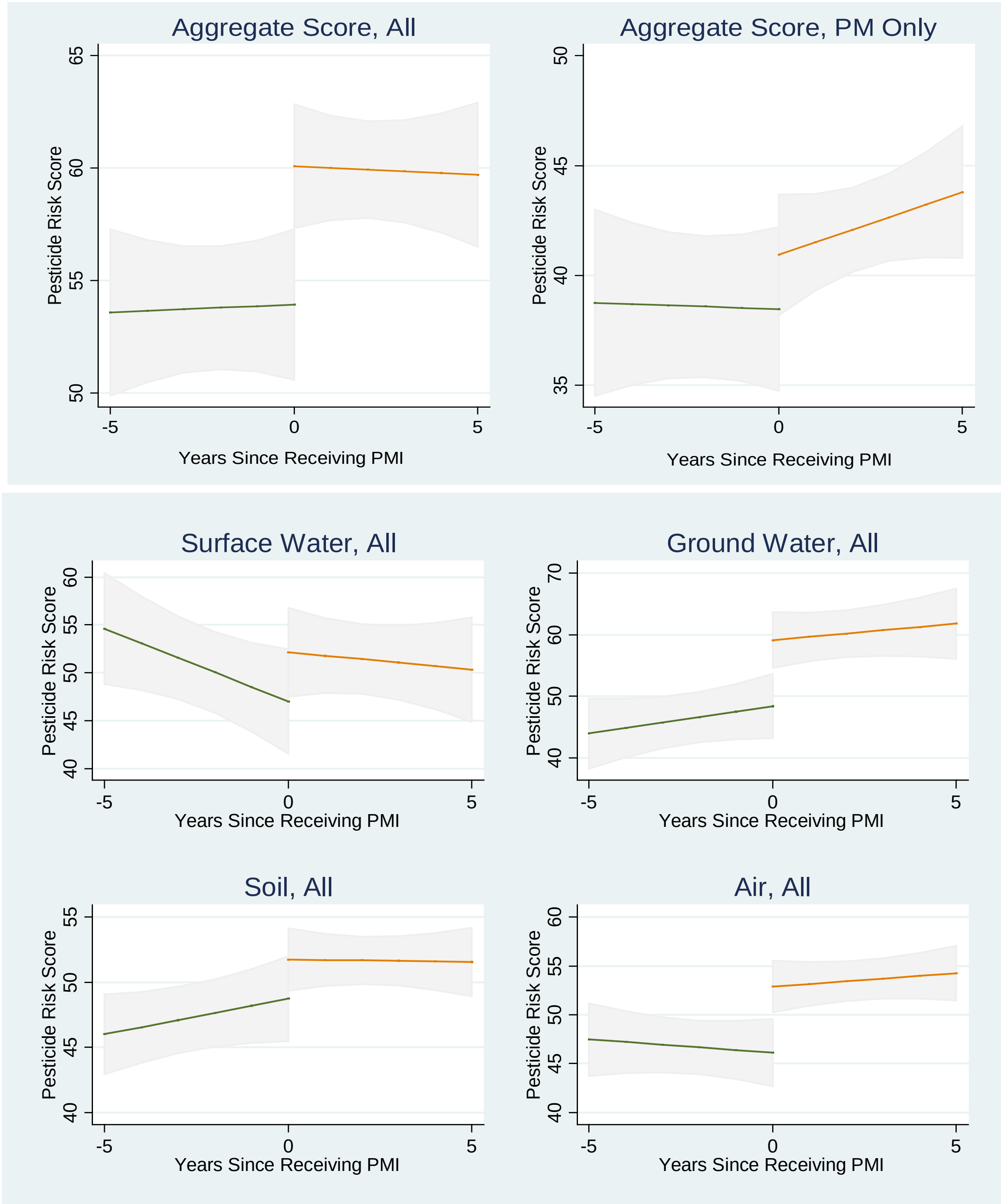

Figure 5 Impact of years since receiving the PMI on PURE risk scores controlling for linear time trend and county fixed effects with 90% confidence intervals. "PM Only" indicates that the risk score is computed only for powdery mildew treatments; otherwise, the risk scores are based on all reported pesticide usage of the growers.

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 Summary of stochastic mixed-integer nonlinear programming model results. With both one and two response dimensions, informed growers reduce sprays (stretch intervals) and are exposed to slightly higher risk of damages as a result. With two response dimensions, informed growers shift to higher potency Y when the PMI is high and value of production is high.

	Low Value (p_g=0.5)							**High Value (p_g=3)**						
	Day					Crop Damages	+ Spray Costs	Day					Crop Damages	+ Spray Costs
	1	2	3	4	5			1	2	3	4	5		
One response dimension: Treatment timing[a]														
PMI (low)	6	5	4	5	4			6	5	4	5	4		
Naïve		X		X		37	41	X	X	X	X	X	220	229
Informed		X				38	40	X			X		224	228
PMI (high)	8	9	10	10	9			8	9	10	10	9		
Naïve		X		X		451	455	X	X	X	X	X	2866	2696
Informed		X		X		451	455	X	X	X	X	X	2866	2696
Two response dimensions: Treatment timing & product choice[b]														
PMI (low)	6	5	4	5	4			6	5	4	5	4		
Naïve	X	Y	X	Y		19	33	X	Y	X	Y	X	112	128
Informed		Y		X		20	27	X	Y	X	Y		113	127
PMI (high)	8	9	10	10	9			8	9	10	10	9		
Naïve	X	Y	X	Y		371	385	X	Y	X	Y	X	2215	2231
Informed	X	Y	X	Y		371	385	X	Y	X	Y	Y	2212	2231

[a] $\boldsymbol{\alpha = 10, \gamma_X = 0.6, p_X = 2, \delta_X = 1, \varphi = 2}$

[b] $\boldsymbol{\alpha = 10, \gamma_X = 0.6, \gamma_Y = 0.7\ p_X = 2,\ p_Y = 5, \delta_X = 1, \delta_Y = 2, \varphi = 2}$

Table 3 Data dimensions

	Number of Surveyed Growers	Number of Plots	Grower-Plot-Years	Grower-Plot-Days[a]	Number of PM treatments		Avg distance to weather station (km)[b]	2007 revenue per ton (average)[c]
					No PMI	With PMI		
North Coast (sub-total)	**31**	**444**	**2,299**	**423,016**	**8,125**	**12,580**		
Napa	8	221	908	167,072	1,283	4,826	4.7	$3,251
Sonoma	19	180	1,103	202,952	6,453	6,453	6.6	$2,081
Mendocino	4	43	288	52,992	389	1,301	25.9	$1,223
Central Coast								
San Luis Obispo	**17**	**66**	**475**	**80,750**	**2,739**	**4,470**	16.5	$1,131
Valley (sub-total)	**19**	**229**	**1,534**	**244,680**	**6,547**	**5,587**		
San Joaquin	9	95	805	120,750	855	4,175	26.5	$341
Fresno	5	55	406	69,020	4,680	33	68.9	$202
Madera	5	79	323	54,910	1,012	1,379	69.4	$202
TOTAL	**86**	**968**	**5,842**	**993,126**	**23,958**	**28,224**	**22.5**	

a. For each grower-plot this includes the number of days during the growing season that are at risk for PM. This PM 'window' within the growing season is region-specific (see Flaherty 1992).

b. This average distance is based on the distance between the plots managed by our surveyed growers and the weather stations that collected the PMI data we use (to which these plots were matched).

c. Source: Grape Crush Report, 2007, USDA / NASS

Table 4 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 5 Spline regression results for pooled regression with plot-year fixed effects and growth phase fixed effects (p-values based on robust standard errors clustered at the plot-year level shown in parentheses).

	Spray {0,1}	Interval	Product choice {0,1} Sul	Product choice {0,1} Syn	Avg. Dose Pctile	Multi Product
North Coast						
PMI	0.017	-1.7	0.017	-0.047	-0.064	0.018
	(0.000)	(0.048)	(0.540)	(0.087)	(0.002)	(0.480)
PMI|Low*Recipient	-0.0041	2.4	-0.061	0.088	0.16	-0.095
	(0.330)	(0.076)	(0.250)	(0.051)	(0.000)	(0.067)
PMI|Mid*Recipient	-0.026	3.100	-0.230	0.270	-0.044	0.018
	(0.004)	(0.178)	(0.013)	(0.002)	(0.397)	(0.841)
PMI|High*Recipient	-0.016	0.930	0.067	-0.045	0.100	-0.014
	(0.001)	(0.438)	(0.163)	(0.338)	(0.000)	(0.761)
PMI*Recipient Pre-Receipt	0.003	0.93	-0.011	0.048	0.11	-0.16
	(0.290)	(0.300)	(0.730)	(0.100)	(0.000)	(0.000)
N=	417523	20705	20705	20705	20705	20705
J (# plot*year)=	2289	2230	2230	2230	2230	2230
R Sq	0.015	0.019	0.22	0.2	0.02	0.046
Central Coast						
PMI	0.0028	-1.7	0.079	-0.039	0.17	0.036
	(0.680)	(0.160)	(0.091)	(0.500)	(0.000)	(0.490)
PMI|Low*Recipient	-0.014	3.6	-0.049	0.025	-0.13	-0.011
	(0.260)	(0.011)	(0.400)	(0.690)	(0.020)	(0.890)
PMI|Mid*Recipient	0.011	0.590	(0.087)	0.046	0.025	0.008
	(0.660)	(0.806)	(0.277)	(0.560)	(0.776)	(0.951)
PMI|High*Recipient	-0.021	0.110	-0.130	0.120	-0.220	0.009
	(0.162)	(0.942)	(0.023)	(0.082)	(0.001)	(0.903)
PMI*Recipient Pre-Receipt	0.001	-0.03	-0.16	0.06	-0.21	0.15
	(0.940)	(0.990)	(0.004)	(0.340)	(0.000)	(0.017)
N=	77906	7209	7209	7209	7209	7209
J (# plot*year)=	466	458	458	458	458	458
R Sq	0.013	0.018	0.31	0.36	0.15	0.16
Valley						
PMI	0.018	-0.89	0.072	-0.07	-0.022	-0.16
	(0.000)	(0.006)	(0.000)	(0.000)	(0.043)	(0.000)
PMI|Low*Recipient	0.04	-0.48	0.0029	-0.044	0.059	0.092
	(0.000)	(0.700)	(0.940)	(0.250)	(0.045)	(0.110)
PMI|Mid*Recipient	-0.047	3.500	-0.380	0.360	-0.092	0.200
	(0.003)	(0.145)	(0.000)	(0.000)	(0.071)	(0.069)
PMI|High*Recipient	-0.022	2.900	0.140	-0.120	0.052	-0.008
	(0.006)	(0.016)	(0.005)	(0.014)	(0.073)	(0.885)
PMI*Recipient Pre-Receipt	-0.006	0.67	-0.02	0.02	0.16	0.21
	(0.350)	(0.570)	(0.610)	(0.490)	(0.000)	(0.007)
N=	234830	12128	12128	12128	12128	12128
J (# plot*year)=	1530	1454	1454	1454	1454	1454
R Sq	0.013	0.032	0.1	0.099	0.027	0.021

Table 6 Spline regression results for pooled regression with plot-year fixed effects and growth phase fixed effects including only growers who switch from not receiving to receiving the PMI (p-values based on robust standard errors clustered at the plot-year level shown in parentheses).

	Spray {0,1}	Interval	Product choice {0,1} Sul	Syn	Avg. Dose Pctile	Multi Product
North Coast						
PMI	0.018	-0.84	-0.0014	0.0045	0.037	-0.11
	(0.000)	(0.003)	(0.930)	(0.750)	(0.001)	(0.000)
PMI|Low*Recipient	-0.0089	0.89	-0.016	0.01	0.01	0.16
	(0.056)	(0.480)	(0.780)	(0.820)	(0.710)	(0.005)
PMI|Mid*Recipient	-0.019	1.500	-0.150	0.120	-0.080	-0.160
	(0.084)	(0.579)	(0.134)	(0.202)	(0.146)	(0.110)
PMI|High*Recipient	-0.026	-1.100	-0.005	0.010	0.056	0.170
	(0.000)	(0.317)	(0.914)	(0.831)	(0.025)	(0.001)
N=	271809	15105	15105	15105	15105	15105
J (# plot*year)=	1496	1456	1456	1456	1456	1456
R Sq	0.014	0.025	0.26	0.24	0.029	0.071
Central Coast						
PMI	0.004	-0.16	-0.0038		0.00068	0.16
	(0.410)	(0.820)	(0.740)		(0.960)	(0.000)
PMI|Low*Recipient	0.11	12	0.33		0.24	0.16
	(0.004)	(0.000)	(0.077)		(0.140)	(0.500)
PMI|Mid*Recipient	-0.130	-4.400	-0.360		-0.250	-0.290
	(0.075)	(0.448)	(0.087)		(0.074)	(0.283)
PMI|High*Recipient	-0.069	5.700	0.110		0.200	-0.300
	(0.100)	(0.018)	(0.242)		(0.039)	(0.006)
N=	27835	2517	2517		2517	2517
J (# plot*year)=	167	159	159		159	159
R Sq	0.018	0.047	0.059		0.041	0.18
Valley						
PMI	0.008	1.5	0.04		0.11	0.062
	(0.160)	(0.340)	(0.120)		(0.002)	(0.360)
PMI|Low*Recipient	0.042	-0.4	-0.01		0.077	-0.35
	(0.007)	(0.930)	(0.960)		(0.440)	(0.025)
PMI|Mid*Recipient	(0.040)	-12.000	0.068		-0.400	0.370
	(0.253)	(0.046)	(0.842)		(0.026)	(0.171)
PMI|High*Recipient	0.027	4.800	0.350		-0.082	-0.120
	(0.220)	(0.195)	(0.007)		(0.368)	(0.424)
N=	28327	1379	1379		1379	1379
J (# plot*year)=	186	171	171		171	171
R Sq	0.016	0.059	0.12		0.049	0.023

Table 7 Summary of level and response differences between PMI recipients and non-recipients.

	North Coast	**Central Coast**	**Valley**
Level differences for PMI recipients			
	Fewer sulfur treatments. More synthetic treatments. Lower sulfur dosage rates. Higher syn. dosage rates.		
Response differences for PMI recipients			
Low PMI [0,30]	Tighten intervals.		Increase synthetic treatments.
Mid PMI [40,50]	Constant sulfur dosage rate. More cocktails.	Higher pr(spray).	Increase synthetic treatments.
High PMI [60,100]	Shift from sulfur to synthetics. Increase sulfur dosage rate. Increase syn. dosage rate. More cocktails.	Stretch intervals. Increase sulfur treatments. Increase sulfur dosage rate. Fewer cocktails.	Fewer cocktails.

Table 8 Mean PURE risk scores for PMI non-recipients and recipients with p-values based on t-test of different means assuming equal variances in parentheses.

		Treatments Included	
Risk Score	**Received PMI**	**All**	**PM Only**
Aggregate	**No (N=582)**	54.8	37.6
	Yes (N=360)	56.3	41.5
		(0.190)	(0.002)
Surface Water	**No**	47.6	34.7
	Yes	49.7	42.5
		(0.360)	(0.001)
Groundwater	**No**	49.2	27.8
	Yes	53	33
		(0.090)	(0.000)
Soil	**No**	47.4	29.3
	Yes	50.7	33.2
		(0.002)	(0.000)
Air	**No**	49.8	32.2
	Yes	49.3	33.2
		(0.620)	(0.300)

Table 9 Results of pesticide use risk as a function of PMI usage with grower random effects, region fixed effects and year fixed effects. P-values based on cluster robust standard errors shown in parentheses. Pesticide use risk scores (dependent variable) are based on all pesticide applications and on only PM treatments separately as indicated by the 'Treatments included' row.

		All		Switchers Only	
	Treatments included:	**All**	**PM Only**	**All**	**PM Only**
Aggregate Risk	**Received PMI {0,1}**	5.55	4.48	5.08	3.3
		(0.069)	(0.170)	(0.004)	(0.120)
	Pre-PMI Receipt {0,1}	-0.23	-0.19		
		(0.940)	(0.960)		
	N=	942	942	591	591
	R2=	0.2	0.2	0.21	0.26
Surface Water Risk	**Received PMI {0,1}**	2.25	6.18	2.99	2.85
		(0.640)	(0.230)	(0.300)	(0.440)
	Pre-PMI Receipt {0,1}	-5.18	-1.99		
		(0.320)	(0.720)		
	R2=	0.42	0.36	0.45	0.36
Groundwater Risk	**Received PMI {0,1}**	14.5	10.3	8.25	2.14
		(0.005)	(0.013)	(0.006)	(0.340)
	Pre-PMI Receipt {0,1}	7.29	7.32		
		(0.190)	(0.100)		
	R2=	0.31	0.27	0.34	0.26
Soil Risk	**Received PMI {0,1}**	5.37	4.87	3.46	2.89
		(0.050)	(0.076)	(0.045)	(0.100)
	Pre-PMI Receipt {0,1}	-1.16	1.79		
		(0.700)	(0.550)		
	R2=	0.12	0.15	0.094	0.17
Air Risk	**Received PMI {0,1}**	2.57	1.04	4.7	4.43
		(0.420)	(0.680)	(0.014)	(0.003)
	Pre-PMI Receipt {0,1}	0.084	-1.96		
		(0.980)	(0.490)		
	R2=	0.16	0.19	0.21	0.33