Pesticide Spraying and Disease Forecasts:
A Dynamic Structural Econometric Model of Grape Growers in California[1]

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Abstract

Grape powdery mildew is an important disease that afflicts grapes and vineyards worldwide, and poses a significant disease management task for grape growers in California. We develop and estimate a dynamic structural econometric model of growers' decisions of whether and when to spray pesticides in response to the Powdery Mildew Index (PMI), a forecasting model to help growers anticipate outbreaks of powdery mildew and time their treatments accordingly. The model is used to determine the factors that affect growers' decisions, including the effect of powdery mildew pressure and the use of the PMI disease forecast information; to examine how the heterogeneity of grower responses to the PMI is affected by production system differences among different groups of growers; and to evaluate the degree of risk aversion of growers in our sample. Our dynamic structural econometric model allows for unobserved heterogeneity in the susceptibility of the variety of grapes grown to powdery mildew. Results show that raisin grape growers have lower relative risk aversion than wine grape growers, and also less variation in the coefficient of relative risk aversion among growers in different counties. We find that growers in Napa perceive that a large share of their varieties are susceptible to a powdery mildew infection. Fresno is the only county where having the PMI disease forecast information increases average welfare for wine grape growers. On the other hand, having the PMI disease forecast information increases average welfare for raisin grape growers in all counties.

Keywords: pesticides, dynamic structural model, unobserved heterogeneity, risk aversion
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1. Introduction

Grape powdery mildew is an important disease that afflicts grapes and vineyards worldwide, and poses a significant disease management task for grape growers in California. Powdery mildew outbreaks happen quickly and can cause significant losses in quality and yield, so the focus of powdery mildew management is its prevention rather than the control of its outbreaks. Growers use pesticides as a tool to manage production risk, and pesticides can decrease the costs of production and increase welfare for both producers and consumers. Growers may use pesticides as a form of insurance and are likely to choose more potent chemicals and over-apply when pest or disease outbreaks are difficult to predict and crop insurance is not easily accessible (Mumford and Norton, 1984).

The Powdery Mildew Index (PMI) is a forecasting model to help growers anticipate outbreaks of powdery mildew and time their treatments accordingly (Thomas, Gubler and Leavitt, 1994; Gubler et al., 1999). The analysis in this paper aims to understand how different types of growers adjust the protocols used to control powdery mildew in response to the PMI disease forecast information and how the heterogeneity of these responses is affected by production system differences among different groups of growers.

We develop and estimate a dynamic structural econometric model of growers' decisions to spray pesticides in response to the PMI disease forecast information. Our model is used to determine the factors that affect growers' decisions, including the effect of powdery mildew pressure and the use of the PMI; to examine how the heterogeneity of grower responses to the PMI is affected by production system differences among different groups of growers; and to evaluate the degree of risk aversion of growers in our sample. We allow the parameters to vary by county; region; years of low, medium, and high disease pressure; and years of low, medium, and high per acre revenue. We also allow for unobserved heterogeneity in the susceptibility of the variety of grapes grown to powdery mildew.

The California grape industry includes three main production sectors: wine, raisin, and table grapes. Each sector has a distinct production process and market mechanisms, and the behavior of the growers during the production process varies according to the end-use of grapes. We apply our dynamic structural econometric model to data on wine grape growers and raisin grape growers in California. While the value per acre of raisin grapes is comparable to the value of lower-end wine grapes, the production systems, varieties, and regional disease pressure are different.

There are several advantages to using a dynamic structural model to model the spraying decisions of grape growers. First, unlike reduced-form models, a structural approach explicitly models the dynamics of spraying decisions. The spraying of pesticides is an investment that requires incurring costs for future gain. Moreover the spraying decision takes place under uncertainty. Since the spraying decision is irreversible, there is uncertainty over the payoffs from spraying, and growers have leeway over the timing of investments, there is an option value to waiting which requires a dynamic model (Dixit and Pindyck, 1994).

A second advantage of our structural model is that it allows us to estimate the effect of each state variable on the expected payoffs from the decisions to spray or not to spray, and, therefore, to estimate parameters that have direct economic interpretations. The dynamic model accounts for the continuation value, which is the expected value of the value function next period. With the structural model it is possible to estimate parameters in the payoffs from the decisions to spray or not to spray, since we can structurally model how the continuation values relate to the payoffs from the decisions to spray or not to spray.

A third advantage of our structural model is that it allows us to estimate the degree of risk aversion exhibited by the growers. In particular, we use a constant relative risk aversion (CRRA) utility function to estimate a grower's coefficient of relative risk aversion.

A fourth advantage of our structural model is that it incorporates unobserved heterogeneity, which in this model represents the susceptibility of the variety of grapes grown to powdery mildew. Our structrural model enables us to estimate the distribution of unobserved susceptibility as well as the effects of varietal susceptibility on payoffs.

A fifth advantage of a structural model is that the parameter estimates from the structural model can be used to simulate counterfactual scenarios. We use the parameter estimates to simulate what would happen if all growers received the PMI disease forecast information, and also to simulate what would happen if no growers received the PMI disease forecast information, and then compare the average grower welfare under the two counterfactual scenarios as a measure of the value to the growers of the PMI disease forecast information.

Our paper contributes to the literature on risk aversion for agricultural producers in several ways. First, we examine the degree of risk aversion of agricultural producers using daily real life production decisions. The structure of the data allows us to evaluate the daily actions of the growers when faced with real life risk to their crop. In addition, due to the richness of the data, we are able to distinguish among various levels of risk to the crop, since we can observe periods of high disease risk. In addition, we estimate the models separately for different groups of growers (wine and raisin), for different counties, and for years grouped by disease pressure or levels of per acre revenue, which allows us to examine the degree of risk aversion exhibited by agricultural producers in various production environments under various magnitudes of expected loss.

The coefficients of relative risk aversion estimated for agricultural producers in previous literature ranges from 0.15 to 1.95, with mean estimates around 0.7 (Cardenas and Carpenter, 2008; Chetty, 2006; Bombardini and Trebbi, 2012; Lins, Gabriel and Sonka, 1981). We estimate the CRRA coefficient to range from 0.4 to 1.4, with most estimated coefficients between 0.4 and 0.7.

Our results show that raisin grape growers have lower relative risk aversion than wine grape growers, and also less variation in the coefficient of relative risk aversion among growers in different counties. We find that growers in Napa perceive that a large share of their varieties are susceptible to a powdery mildew infection. Fresno is the only county where having the PMI disease forecast information increases average welfare for wine grape growers. On the other hand, having the PMI disease forecast information increases average welfare for raisin grape growers in all counties.

The balance of this paper proceeds as follows. We review the previous literature in Section 2. We describe our dynamic structural econometric model in Section 3. Section 4 describes our data. Section 5 presents our results. We use our estimated parameters to run counterfactul simulations in Section 6. Section 7 concludes.

2. Literature Review

Economic threshold models form a basis of much of the Integrated Pest Management literature. In theoretical models of optimal pest management, the economic threshold is defined as the pest population density at which control measures should be implemented to prevent crop injury (Headley, 1971; Mumford and Norton, 1984). The precise definition of an economic threshold in the context of pest management is the pest population density that prevents the pest levels from reaching the economic injury level taking into account grower reaction times and pest population response to control measures (Pedigo, Hutchins and Higley, 1986). Another definition used for modeling optimal timing and quantity of pesticide application is the pest density where the marginal value product of damage control equals the marginal cost of control (Hall and Norgaard, 1973).

Other models have extended the dynamic pesticide application framework to incorporate the need for multiple treatments (Bor, 1995; Harper et al., 1994). Bioeconomic models that combine knowledge of plant development and pest population dynamics at every stage of the season allow for more precise modeling of optimal pest management including the evaluation of spatial externalities from grower decisions (Harper et al., 1994; Musser, Nyrop and Shelton, 2006; Olson and Badibanga, 2005; Atallah et al., 2015). Bioeconomic models also consider multiple pest control options such as broad spectrum pesticide application versus using populations of natural enemies.

Fungal disease, such as powdery mildew, is not subject to some of the variables relevant to insect pest control since there are no natural enemies and since the fungal population develops differently from an insect pest population. However, the disease management decisions made by the grower are subject to a similar decision process. The grower makes discrete investment decisions each period when a threat of a disease is present and this decision-making process affects the final outcome. The discrete investment process is especially relevant for powdery mildew control because each spraying decision has no effect beyond the pesticide effectiveness window (usually 7 to 21 days). A regenerative optimal stopping model (Rust, 1987) provides a convenient framework for this type of decision process.

This paper builds on previous work by Lybbert, Magnan and Gubler (2016), who examine the changes in powdery mildew treatment strategies of wine grape growers in response to the PMI disease forecast information. The authors use a reduced-form econometric analysis to examine the response of the growers along three dimensions of pesticide applications: timing of sprays, chemical choice, and dosage. They find significant heterogeneity in response among growers along all three dimensions of adjustment. The results of their analysis suggest that wine grape growers with high-value crops are more likely to increase the dosage and choose more potent pesticides in response to forecasts of high infection risk, while wine grape growers with crops of lower value are more likely to extend the intervals between treatments during periods when the disease pressure is forecast to be low. The authors suggest several sources of heterogeneity that could be affecting grower behavior but were not explicitly addressed in the study: differences in production systems, crop value, and varietal susceptibility to powdery mildew infections.

This paper builds on the previous reduced-form analysis by Lybbert, Magnan and Gubler (2016) developing and estimating a dynamic structural econometric model of growers' decisions to spray pesticides in response to the PMI disease forecast information. Our model addresses some sources of observed and unobserved heterogeneity mentioned in Lybbert, Magnan and Gubler (2016), such as differences in harvest value of crops, differences between raisin and wine grape production systems, and susceptibility of grape varieties to powdery mildew. In addition to the existing dataset of wine grape growers used in Lybbert, Magnan and Gubler (2016), the analysis in this paper also includes additional data from a survey of growers of raisin grapes. These data are used to examine the heterogeneity in responses by grape growers based on differences in end-use of grapes grown and regional disease pressure. The value per acre of raisin grapes is comparable to the value of lower-end wine grapes, but the production systems, varieties, and regional disease pressure are different. Including raisin growers allows for the analysis of another source of heterogeneity in pesticide applications of grape growers: production heterogeneity of wine versus raisin grape growers in the same county.

The dynamic structural econometric model used in this paper applies the nested fixed-point maximum likelihood estimation approach developed by Rust (1987, 1988). Dynamic structural econometric models have been adapted for many applications, including bus engine replacement (Rust, 1987), optimal replacement of dairy livestock (Miranda and Schnitkey, 1995), nuclear power plant shutdown (Rothwell and Rust, 1997), water management (Timmins, 2002), insecticide treated nets (Mahajan and Tarozzi, 2011), rural labor supply (Duflo, Hanna and Ryan, 2012), land use in agriculture (Scott, 2013), air conditioner purchases (Rapson, 2014), wind turbine shutdowns and upgrades (Cook and Lin Lawell, 2019), copper mining decisions (Aguirregabiria and Luengo, 2016), crop disease control (Carroll et al., 2019b), vehicle scrappage programs (Li and Wei, 2013), supply chain externalities (Carroll et al., 2019a), organ transplant decisions (Agarwal et al., 2018), agricultural productivity (Carroll et al., forthcoming), consumer stockpiling (Ching and Osborne, 2018), the adoption of rooftop solar photovoltaics (Feger et al., 2017; Langer and Lemoine, 2018), and vehicle ownership and usage (Gillingham et al., 2016). Connault (2016) studies the econometrics of dynamic discrete choice models with unobserved states. In this paper, we use a dynamic structural econometric model with unobserved heterogeneity based on a model developed by Arcidiacono and Miller (2011).

3. Dynamic Structural Econometric Model

In our model, each grower makes discrete investment decisions each period that a threat of a disease is present, and it is this decision-making process that affects the final outcome. The discrete investment process is especially relevant for powdery mildew control because each spraying decision has no effect beyond the pesticide effectiveness window (usually between 7 and 21 days). A regenerative optimal stopping model (Rust 1987) provides a convenient framework for this type of decision process.

The grower decision to spray or not to spray against powdery mildew follows a decision process similar to that described by Rust (1987). Each day the grower assesses the probability of a powdery mildew infection based on the maximum value of the PMI over the past 7 days, which measures disease pressure risk; the interval since the last pesticide application relative to the protective strength of the chemical last applied, which describes the degree of current crop protection; and the susceptibility of the variety of grapes grown to powdery mildew. The grower then makes the decision of whether to spray the pesticide, and how much and which pesticide to spray.

Unlike a durable good that depreciates over time, the grape crop has an expected value that must be maintained (or increased) by proper input use and disease management. We assume that the grower starts the season knowing the approximate expected value of the crop at harvest time. Because of the nature of the grape crop, the replacement decision in the optimal stopping model is actually a maintenance decision by the grower. Maintenance in this case is preventive spraying against powdery mildew. If the grower decides not to spray, there are no maintenance costs, but the grower then risks a powdery mildew outbreak.

The grower makes the spraying decisions with a definite time horizon in mind. The natural finite time horizon in this case ends at harvest time and the grower usually knows the harvest and sale period to within a few weeks. This is different from most dynamic optimal stopping models since many of them deal with maintenance and replacement of durable goods or -- in the case of agriculture -- livestock, where the time horizon is infinite.[2]

A typical grower possesses one or more plots. A grape vineyard operation may contain a single plot, or multiple plots, and a grower may also have multiple vineyards.[3] We assume that the grower makes separate and independent application decisions for each plot. The plots are often adjacent to each other, but they can also be apart. Spatial spillovers between plots are not a concern because powdery mildew outbreaks are generally localized. For example, there may be powdery mildew present in one corner of the plot, not another. Powdery mildew does not spread the way a pest would, as powdery mildew spores are always present in pretty much all grape vineyards and activated by weather (Gubler et al., 2008).

Because raisin and table grape production are geographically clustered, the weather information that serves as a basis for calculating the PMI is unlikely to vary significantly between growers in the same region. However, this is not the case for wine grape growers in the coastal counties, which are subject to microclimates. The structure of the data allows us to model grower spraying decisions for each plot, so it is possible to explore the possibility that unobservable plot-level heterogeneity is relevant to grower decisions.

We begin with a simple model that explains spraying decisions of a single grape grower in response to the risk of powdery mildew infection indicated by the Powdery Mildew Index (PMI). Each day t the grower decides whether to apply pesticides to prevent a powdery mildew outbreak. The grower has a choice of which type z of pesticide to apply. The grower has to make this decision for each of T periods, starting with t_0, the first day of possible powdery mildew infection, and ending with T, the day of the harvest.

Since some chemicals have similar protective power, as well as similar costs, we can group the spray choice into three categories based on the degree of protection they provide for each level of PMI. In this model, $a_t = 0$ if the grower does not spray at time t; $a_t = 1$ if the grower sprays

[2] The time horizon of the production process can be modeled as infinite when the production process is ongoing and does not have a definitive growing season (e.g., dairy production) and when the inputs can be replaced during the production process (e.g., a bus engine or a dairy cow). For crops such as grapes, however, the production process ends with harvest each season and the value of the harvest depends on the maintenance of the crop throughout the entire growing season. Thus, the time horizon is finite for daily grape growing decisions.

[3] A vineyard operation is a business entity, which may contain one or more distinct plots. we use the term ‘plot' to define a plot with grapes, which is described as a separate unit in the application for a permit to apply pesticides. Each plot has a unique physical description and a unique identifier, including a location identifier using the Public Land Survey System of coordinates (PLSS), in the Pesticide Use Report database.

with sulfur or contact materials at time t; $a_t = 2$ if the grower sprays with synthetic fungicides (sterol inhibitors, strobilurins, or cell-signaling inhibitors) at time t; and $a_t = 3$ if the grower sprays with other powdery mildew treatment products at time t.

Powdery mildew outbreaks happen as a result of spore procreation during favorable weather so weather on the day of and several days preceding the spraying decision is the primary source of a grower's expectation about the probability of an outbreak. The weather state is summarized in the daily value of the Powdery Mildew Index.

The grower chooses a sequence of spraying decisions $\{a_0, a_1, a_2, a_3, ..., a_T\}$ to maximize the discounted present value of the entire stream of per-period utility $u(\cdot)$, yielding the following dynamic optimization problem:

$$\max_{\{a_t\}} E \sum_{t=0}^{T} \beta^t u(x_t, \nu, \varepsilon_t, a_t; \theta), \tag{1}$$

where x_t is a vector of state variables that influence the probability of powdery mildew infection on a given day; ν is an unobserved time-invariant state variable measuring susceptibility of the variety of grapes grown to powdery mildew; ε_t is vector of random shocks $\varepsilon_t(a_t)$ to per-period utility, one for each possible action a_t in the action set, that is observed by the grower, but not by the econometrician; and θ is the vector of parameters to be estimated.

One exogenous state variable in x_t is PMI_t, the maximum value of the Powdery Mildew Index over the past 7 days. The daily PMI measures the risk of an outbreak if no treatment were administered (i.e., if the crop were completely unprotected). PMI_t is assumed to evolve as a finite state first-order Markov process, where $x_{t+1} \overset{iid}{\sim} F_x(\cdot \mid x_t)$. The values x_{t+1} of the exogenous state variable PMI_t are assumed to be independently and identically distributed and the probability distribution depends only on the realization of x_t in time t and not on anything that happened before time t (Dixit and Pindyck, 1994).

A second exogenous state variable in x_t is the duration ρ_z of pesticide protection in days given the current disease pressure, for each pesticide z. Starting with the day after application, the protective power of the chemical decreases each day as the interval since application approaches the maximum days of protection. For some chemicals, the duration of protection ρ_z also changes with current PMI values.

A third exogenous state variable in x_t is the spraying cost $S(a_t)$ for each pesticide choice a_t. A fourth exogenous state variable in x_t is the per acre crop value PY_t. The exogenous crop value state variable PY_t does not change within a single year, but may change from year to year. The value of the crop is based on the grape varieties grown, their annual price per ton, and per acre yields.

The endogenous state variable in x_t is the interval i_t since last spray. The interval since last spray, measured in days, evolves as follows:

$$i_{t+1} = \begin{cases} i_t + 1 & \text{if } a_t = 0 \\ 1 & \text{if } a_t \geq 1 \end{cases} . \tag{2}$$

In addition to the observed state variables x_t, the probability of powdery mildew infection and therefore growers' pesticide use decisions are also affected by ν, an unobserved time-invariant state variable measuring susceptibility of the variety of grapes grown to powdery mildew.

Expected monetary losses resulting from a powdery mildew infection are given by the expected crop loss function $c(x_t, \nu, \theta)$, which incorporates the probability of an outbreak as well as the net loss (salvage value minus crop loss) in the case of an outbreak.

Spraying against powdery mildew allows the grower to avoid crop losses that will result from the infection. If the grower chooses to spray ($a_t \geq 1$) on day t, then the expected loss from powdery mildew on day t is equal to zero, and the grower instead incurs spraying costs $S(a_t)$.

We assume that the expected per acre crop value PY_t stays constant throughout the year for each grower, and therefore that growers have perfect foresight regarding the expected revenue per acre for a particular year. We also assume that growers are able to borrow in order to smooth out their annual revenue each day of the growing season. Since the annual revenue per acre is PY, we assume that the grower earns (or can borrow) an average daily revenue of approximately PY/T each day of the *T*-day long growing the season. Given that many wine and raisin grape growers sell their grapes under pre-determined contracts (Fuller, Alston and Sambucci, 2014), our assumptions on annual revenue are not unrealistic.

The per-period utility $u(x_t, \varepsilon_t, a_t; \theta)$ a grower receives on any given day *t* from making a particular decision a_t is the average daily revenue minus the expected losses and costs faced by the grower from that decision, and is given by:

$$u(x_t, \varepsilon_t, a_t; \theta) = \begin{cases} f\left(PY_t / T - c(x_t, \nu; \theta)\right) + \varepsilon_t(0) & \text{if } a_t = 0 \\ f\left(PY_t / T - S(a_t)\right) + \varepsilon_t(a_t) & \text{if } a_t \geq 1 \end{cases}. \tag{3}$$

We estimate several different utility functions which allow for varying degrees of risk aversion: linear utility, logarithmic utility, square root utility, utility with PMI squared, and CRRA utility. Linear utility assumes risk neutrality, logarithmic and square root utilities assume some degree of risk aversion, and CRRA utility allows variation in the degree of risk aversion among the different groups of growers in the sample. Characterizing the risk preferences of growers can help one understand some of the decisions growers make when faced with potential losses from a disease outbreak.

In particular, we examine, compare, and test between different functional forms for the per-period utility, including linear utility $\left(f(X) = X\right)$, linear utility with an additional term for PMI_t squared, log utility $\left(f(X) = \log(X)\right)$, and square root utility $\left(f(X) = \sqrt{X}\right)$. We also consider a constant relative risk aversion (CRRA) utility, in which the per-period utility would be given by:

$$u(x_t, \varepsilon_t, a_t; \theta) = \begin{cases} (1-\gamma)^{-1}(PY_t / T - c(x_t, \nu; \theta))^{1-\gamma} + \varepsilon_t(0) & \text{if } a_t = 0,\ \gamma \neq 1 \text{ and } \gamma > 0 \\ (1-\gamma)^{-1}(PY_t / T - S(a_t))^{1-\gamma} + \varepsilon_t(a_t) & \text{if } a_t \geq 1,\ \gamma \neq 1 \text{ and } \gamma > 0 \\ \ln(PY_t / T - c(x_t, \nu; \theta)) + \varepsilon_t(0) & \text{if } a_t = 0 \text{ and } \gamma = 1 \\ \ln(PY_t / T - S(a_t)) + \varepsilon_t(a_t) & \text{if } a_t \geq 1 \text{ and } \gamma = 1 \end{cases}, \tag{4}$$

where γ is the coefficient of relative risk aversion.

We use likelihood ratio tests to determine which utility function best fit the spraying behavior of the growers. Because the results of likelihood ratio tests explained below and presented in Appendix B show that CRRA utility provides the best fit to the data, we use the CRRA utility function to examine the variation in the degree of risk aversion among different groups of growers, under various degrees of disease risk, and for years of different revenue levels.

We use the following simple specification for the expected loss of crop value $c(x_t, \nu, \theta)$ from powdery mildew, which incorporates the probability of an outbreak as well as the net loss (salvage value minus crop loss) in the case of an outbreak:[4]

$$c(x_t, \nu; \theta) = \theta_1 PMI_t + \theta_2 \, i_t / \rho_Z + \theta_3 \nu \, . \tag{5}$$

Since the probability of an outbreak depends on the value of the PMI_t, the maximum PMI observation over the past 7 days, and is higher the higher the PMI_t, we expect that $\theta_1 > 0$, unless a grower relies heavily on a calendar schedule for pesticide sprays, in which case the coefficient on the PMI_t may be negative. This possibility is discussed in more detail below. The probability of an outbreak is an increasing function of the interval i_t since last spray because the larger the interval, the less protected a crop is from the outbreak given the PMI, and because once the interval i_t since last spray increases past the recommended maximum days of protection ρ_Z, the crop is completely unprotected. We therefore expect that $\theta_2 > 0$. Since the unobserved time-invariant state variable ν measures susceptibility of the variety of grapes grown to powdery mildew, we expect $\theta_3 > 0$, since susceptibility would increase the probability and damage from infection.

The specification of the cost function above places equal weight on intervals throughout the entire season included in the data. The data are standardized so that all seasons have the same number of days ($T = 245$ days). The beginning of the season is March 1st (day 60 of the year or day 1 of the growing season). However, growers do not start spraying on March 1st and instead start spraying on some day in the first two or three weeks of March, usually at budbreak. We assume that the season for powdery mildew control follows suggested calendar of disease treatment timing for six different regions within California in Bettiga (2013). The first spray of each season is applied based on the timing of a growing season for that particular year and is not affected by the PMI. Therefore, the probability of an outbreak restarts at the beginning of each season once the first spray has been made.

In addition to variations in timing of the first spray of the season, the growers also stop spraying at different times during the growing season. Depending on the grape variety, the harvest

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[4] For the specification using linear utility with an additional term for PMI_t squared, the expected loss of crop value is given by: $c(x_t, \nu; \theta) = \theta_1 PMI_t + \theta_2 \, i_t / \rho_Z + \theta_3 \nu + \theta_4 PMI_t^2$.

can start as early as the end of August and as late as November. Therefore, growers who harvest grapes early show very large intervals since last spray towards the end of the season (100 days or more), while the weather data still indicate high probability of infection. Therefore, the model only includes the intervals made between the first and the last sprays of the growing season and does not include any intervals after the last spray of the season was observed.

We model the growers as being able to borrow in order to smooth out their annual revenue each day of the growing season for several reasons. First, if we do not assume that grape growers receive any daily revenue on days before the harvest, then they will only incur costs (either the expected loss from a powdery mildew outbreak if they do not spray, or the spraying costs if they do spray) on each day before the harvest. Since CRRA, log, and square root utility functions $f(X)$ are undefined when X is negative, we would not be able to use CRRA, log, and square root utility functions to model per-period utility if growers only incur costs on all days before the harvest. As analyzing the risk aversion of growers is among the objectives of our paper, we therefore model growers as being able to borrow in order to smooth out their annual revenue each day of the growing season. A second reason we assume that growers are able to borrow in order to smooth out their annual revenue each day of the growing season is that when we ran the model with unobserved heterogeneity and linear utility assuming instead that the crop revenue PY was not received until the last day of the season (the harvest date T), we were unable to identify the coefficient on unobserved heterogeneity, which did not vary much from the initial guess. Thus, since analyzing unobserved heterogeneity and analyzing the risk aversion of growers are both among the objectives of our paper, we model growers as being able to borrow in order to smooth out their annual revenue each day of the growing season. Given that many wine and raisin grape growers sell their grapes under pre-determined contracts (Fuller, Alston and Sambucci, 2014), our assumption that growers have perfect foresight of the expected revenue per acre for a particular year is not unrealistic.

The spraying decision a_t in each period depends only on the current values of the state variables x_t, ν , and ε_t. The decision process can be described as a decision rule $\mu(x_t,\nu,\varepsilon_t)$; a sequence $\pi_T=(\mu_0,\mu_1,...,\mu_t)$ of decision rules is a spraying policy. The optimal policy is the one that maximizes the grower's discounted present value of the entire stream of per-period utility, as given by the following dynamic optimization problem:

$$\max_{\pi_T=(\mu_0,\mu_1,\ldots,\mu_t)} \mathrm{E}\left[\sum_{t=0}^{T}\beta^t u(x_t,\nu,\varepsilon_t,\mu_t(x_t,\nu,\varepsilon_t);\theta)\,|\,x_0,\nu\right]. \tag{6}$$

The value function for each time t is given by the following Bellman equation:

$$V_t(x,\nu,\varepsilon)=\max_a\left\{u(x,\nu,\varepsilon,a;\theta)+\beta E\left[V_{t+1}(x',\nu,\varepsilon')\,|\,x,\varepsilon\right]\right\}, \tag{7}$$

where x and ε are the current values, and x' and ε' are the future values, of the state variables and shocks. Producers observing the current state of (x,ε) will choose a to maximize the current utility plus the discounted value of the expected future utility. The dynamic programming problem can be solved via backwards iteration starting from the harvest period T to calculate the value function $V_t(x,\nu,\varepsilon)$ for each period *t*. The terminal value V_{T+1} at the end of the growing season is set to 0 to reflect that growers do not benefit from the crop past the harvest date T, and therefore would not spray on day T.

The vector of parameters to be estimated is $\theta=(\theta_1,\theta_2,\theta_3,\gamma)$. The discount factor β is set to two different values. We use a daily discount factor of $\beta=0.9$ to examine a model that implies an annual discount factor that is close to zero. In this model, only payoffs received up to a month in the future factor into the decision making process by the grower. This version of the model (Model 1) represents a scenario in which the decision-making process of the grower is more myopic.

Since management of powdery mildew relies on prevention, a completely myopic model may be an oversimplification. We therefore also examine a model with a large daily discount factor, as it allows the decision process to incorporate future payoffs from current decisions. In this more dynamic model, we estimate the model with a discount factor set to β = 0.9996, which is equal to an annual discount factor of approximately 0.9. This version of the model (Model 2) represents a more dynamic scenario.

Both Model 1 and Model 2 model the decision-making process as dynamic and vary only in the degree to which the future payoffs factor into the present decision-making. As the discount factor is not identified in this model, we do not estimate a discount factor for growers. Instead, we conduct a likelihood ratio test between these two scenarios to determine which type of process is a better fit for the decisions observed in the data.

We assume that errors ε_t follow an extreme value distribution conditional on the spraying decision a_t. We also assume conditional independence:

$$\Pr(x_{t+1}, \varepsilon_{t+1} \mid \nu, a_t; \theta) = \Pr(x_{t+1} \mid x_t, a_t; \theta) \Pr(\varepsilon_{t+1} \mid \theta). \tag{8}$$

A standard assumption in many dynamic structural models, our conditional independence assumption implies that the evolution of the observed state variables x_t does not depend on the particular realization of the idiosyncratic shocks ε_t to the utility of individual growers from each possible action choice regarding spraying. For the exogenous state variables PMI_t, the duration ρ_z of pesticide protection, the spraying costs $S(a_t)$ for each pesticide choice a_t, and per acre crop value PY_t, the conditional independence assumption makes sense since the evolution of these exogenous variables is independent of any unobservable idiosyncratic shock to the individual grower. For the endogenous state variable, the interval i_t since last spray, the conditional independence assumption makes sense since since the interval i_t since last spray will evolve deterministically depending on the action choice of the grower, and its evoluation does not additionally depend on any unobservable idiosyncratic shock to the individual grower.

Letting $u_0(x, \nu, a; \theta)$ denote the deterministic component of the per-period utility, which is assumed to be linearly separable from the stochastic component $\varepsilon(a)$, the Bellman equation can then be rewritten as:

$$V_t(x, \nu, \varepsilon) = \max_a u_0(x, \nu, a; \theta) + \varepsilon(a) + \beta E\left[V_{t+1}(x', \nu, \varepsilon') \mid x, a\right]. \tag{9}$$

The continuation value $E\left[V_{t+1}(x', \nu, \varepsilon') \mid x, a\right]$ is the expectation of the value function next period conditional on this period's state (x, ν, ε) and decision a. The continuation value is denoted with $U_t(x, \nu, a)$. Substituting this expression into the Bellman equation, we obtain:

$$V_t(x, \nu, \varepsilon) = \max_a u_0(x, \nu, a; \theta) + \varepsilon(a) + \beta U_t(x, \nu, a). \tag{10}$$

Given the assumed distribution of ε, the probability of the grower making a spraying decision a conditional on observed state x, unobserved state ν, and parameter vector θ is a conditional choice probability given by the following multinomial logit formula:

$$\Pr_\tau(a_t \mid x_t, \nu; \theta) = \frac{\exp\left[u_0(x_t, \nu, a_t; \theta) + \beta U_t(x_t, \nu, a_t)\right]}{\sum_{\tilde{a}} \exp\left[u_0(x_t, \nu, \tilde{a}; \theta) + \beta U_t(x_t, \nu, \tilde{a})\right]}. \tag{11}$$

The likelihood function for the entire sample is:

$$L(\theta) = \prod_{t=0}^{T} \frac{\exp\left[u_0(x_t, \nu, a_t; \theta) + \beta U_t(x_t, \nu, a_t)\right]}{\sum_{\tilde{a}} \exp\left[u_0(x_t, \nu, \tilde{a}; \theta) + \beta U_t(x_t, \nu, \tilde{a})\right]}. \tag{12}$$

From the extreme value distributional assumption for ε, $U_t(x,\nu,a)$ is given by:

$$U_t(x,\nu,a) = E\left[\ln\left(\sum_{a'} \exp\left(u_0(x',\nu,a';\theta) + \beta U_{t+1}(x',\nu,a')\right)\right) | \, x,\nu,a\right]. \tag{13}$$

Since this is a finite time horizon problem, we solve for $U_t(x,\nu,a)$ via backwards induction from last period. The growing season in this case ends with the harvest, which gives the continuation value of zero at time T ($U_T(x,\nu,a) = 0$). Therefore,

$$U_{T-1}(x,\nu,a) = E\left[\ln\left(\sum_{a'} \exp\left(u_0(x',\nu,a';\theta)\right)\right) | \, x,\nu,a\right]. \tag{14}$$

One of the potential sources of unobserved heterogeneity in this model is the variety grown by the grower on a particular plot. Grapevines vary in how susceptible they are to powdery mildew infection and this susceptibility can influence the growers' spraying decisions, especially if the grapes are high value.

Variety-specific susceptibility can also be conditional on the intended use of the crop. The effect of powdery mildew on the sugar content and the appearance of the berries is much more important if the grapes are to be sold fresh as table grapes and so the decrease in crop value is greater if we are looking at the table grape crop.

We apply the expectation maximization (EM) algorithm to the model to determine how heterogeneity in disease susceptibility may influence the growers' decision to treat, following Arcidiacono and Miller (2011). In the model below, P_z denotes the conditional choice probabilities of spraying for each pesticide z. We define P_v as the probability of the grape variety being susceptible to powdery mildew:

$$P_v = \Pr(v). \tag{15}$$

Given that a_n and x_n denote the entire vector of observations of actions and states, respectively, over all days for plot $n \in \{1,...N\}$, q_{nv} is defined as the conditional probability that plot n is in unobserved state ν:

$$q_n = \Pr(v \,|\, a_n, x_n, i_n). \tag{16}$$

The Expectation-Maximization (EM) Algorithm is then used to estimate (θ, P_v, P_z) by iterating over the following Expectation Step (E step) and Maximization Step (M step) over multiple iterations m until convergence.

For each iteration m, in the Expectation Step (E step), we calculate the conditional probability q_{nv} that plot n is in state v. To do this, we first form the likelihood $l(a_{nt} \mid x_{nt}, v; \theta)$ for each observation as follows:

$$l(a_{nt} \mid x_{nt}, v; \theta) = \frac{\exp\left[u_0(x_{nt}, v, a_{nt}; \theta) + \beta U_t(x_{nt}, v, a_{nt})\right]}{\sum_{\tilde{a}} \exp\left[u_0(x_{nt}, v, \tilde{a}; \theta) + \beta U_t(x_{nt}, v, \tilde{a})\right]}. \tag{17}$$

We then use the likelihood $l(a_{nt} \mid x_{nt}, v; \theta)$ for each observation to update the conditional probability q_{nv} that plot n is in unobserved state v using Bayes' rule:

$$q_{nv}^{(m+1)} = \frac{Pv^{(m)} \prod_{t=1}^{T} l(a_{nt} \mid x_{nt}, v; \theta^{(m)})}{\sum_{v'=0}^{1} Pv'^{(m)} \prod_{t=1}^{T} l(a_{nt} \mid x_{nt}, v'; \theta^{(m)})}. \tag{18}$$

We update the population probability P_v of being in unobserved state v as follows:

$$P_v^{(m+1)} = \frac{1}{N} \sum_{n=1}^{N} q_{nv}^{(m+1)}. \tag{19}$$

Finally, we update $P_z(x, v)$ using weighted average of the data:

$$P_z^{(m+1)}(x, v) = l(a_{nt} = z \mid x_{nt}, v; \theta^{(m)}). \tag{20}$$

In the Maximization Step (M Step), we solve for θ^{m+1} using maximum likelihood estimation, taking $q_{nv}^{(m+1)}$ as given:

$$\theta^{(m+1)} = \arg\max_{\theta} \sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{v=0}^{1} q_{nv}^{(m+1)} \ln l(a_{nt} \mid x_{nt}, v; \theta). \tag{21}$$

We estimate (θ, P_v, P_z) by iterating the E step and the M step until convergence.

We estimate standard errors using a non-parametric bootstrap. Grower-years are randomly drawn from the data set with replacement to generate 100 independent panels each with the same number of grower-years as in the original data set. The structural model is run on each of the panels. The standard errors are then formed by taking the standard deviation of the estimates from each of the random samples.

Identification of the parameters θ comes from the differences between per-period payoffs across different action choices, which in finite horizon dynamic discrete choice models are identified when the discount factor β, the distribution of the choice-specific shocks ε_t, and the final period continuation value $U_T(\cdot)$ are fixed (Abbring, 2010; Magnac and Thesmar, 2002; Rust, 1994). In particular, the parameters in our model are identified because each term in the per-period utility $u(x_t, \varepsilon_t, a_t; \theta)$ given in Equations (3) and (4) depends on the action a_t being taken at time *t*, and therefore varies based on the action taken; as a consequence, the parameters do not cancel out in the differences between per-period utilities across different action choices and are therefore identified. For example, the parameters θ in the expected loss of crop value $c(x_t, \nu, \theta)$ from powdery mildew only appear in the per-period utility from not spraying, and are therefore identified in the difference in the per-period utility from not spraying and the per-period utility from spraying.

4. Data

We apply our dynamic structural model to a daily panel set on wine grape growers and raisin grape growers in California that includes all pesticide applications made on a specific plot over the course of 12 to 15 years, as well as corresponding powdery mildew pressure observations from nearby stations. The starting point of this dataset consists of two surveys administered to a sample of wine grape growers (2008) and raisin grape growers (2010). The survey covers the period 1997-2007 for wine grapes and the period 1997-2010 for raisin grapes. The survey data include information on whether a particular grower has received the Powdery Mildew Index for her vineyard in the preceding 12 to 15 years, and demographic information about the vineyard owner or operator. The dataset constructed using the survey of wine grape growers was previously used by Lybbert, Magnan and Gubler (2016). The same methodology and data sources were used to assemble the dataset for raisin grape growers: pesticide application data were assembled from the Pesticide User Reports (PUR) using individual operator identification numbers (grower IDs) provided by the growers. Daily observations of the PMI from the California Irrigation

Management Information System (CIMIS) weather station network were matched to each plot using plot location identifiers contained in the PUR reports.[5]

The growers in the final sample fall into three of the five major grape growing regions in California: North Coast region (Napa, Sonoma, and Mendocino counties), Central Coast region (San Luis Obispo county) and Central Valley region (San Joaquin, Fresno, Madera, and Tulare counties). Raisin grape growers are located in the Central Valley region only. A detailed discussion of the differences in climate and crop value among the major growing regions is presented in Sambucci (2015). The dimensions of the resulting dataset are presented in Table A.1 in Appendix A.

Previous reduced-form analysis of powdery mildew management programs of the surveyed wine grape growers by Lybbert, Magnan and Gubler (2016) has established a wide heterogeneity of responses among growers in the three regions as well as differences in powdery mildew management with and without the use of the PMI. To account for heterogeneity of growers within each region, we allow the model parameters to vary by county. PMI provides an indicator of powdery mildew outbreak risk based on the current weather (mostly, temperature), so we expect the PMI observations to be relevant for modeling decisions even for growers who do not receive PMI, since all growers still observe weather and know the type of weather favorable to powdery mildew outbreaks. In fact, prior to the development of PMI, the conventional wisdom the growers followed was "if you like the weather, so does powdery mildew" (Lybbert, Magnan and Gubler, 2016). We therefore include observations of the PMI as a proxy for weather in the model for growers who do not use the official PMI index and the combined dataset of users and non-users, although we expect the coefficient on the PMI to be of smaller magnitude for growers who do not use the PMI.

We consider five observed state variables that affect grower decisions: PMI_t, the maximum value of the Powdery Mildew Index over the past 7 days; the duration ρ_z of pesticide protection in days given the current disease pressure for each pesticide z; the interval i_t since last spray; the per acre crop value PY_t; and the spraying costs $S(a_t)$ for each pesticide choice a_t.

[5] PUR reports include PLSS (Public Land Survey System) coordinates for each plot. PLSS coordinates were converted to GPS coordinates and matched to daily PMI data from the nearest available weather station for each year. For a detailed explanation of the PLSS system of coordinates, please see http://geology.isu.edu/geostac/Field_Exercise/topomaps/plss.htm. Additional information on matching plot coordinates with weather station data can be found in Sambucci (2015).

The exogenous state variable PMI_t, the maximum value of the Powdery Mildew Index over the past 7 days, ranges in value from 0 to 100 and is discretized into three bins: 1 = low (PMI_t values between 0 and 30), 2 = moderate (PMI_t values of 31–59) and 3 = high (PMI_t values of 60 or greater). The data on PMI_t comes from weather stations near the plots of the surveyed growers.

Figure 1 shows the distribution of high, medium, and low powdery mildew pressure days by county and year, as well as average values for all counties. To account for years of varying powdery mildew pressure, the model is estimated separately for years of low, medium, or high powdery mildew pressure, ranked relative to the average distribution of categories of the PMI observed for a specific county. Alternatively, the years of low, medium, or high powdery mildew pressure can be ranked according to the average observed powdery mildew pressure for all counties together, with similar results.

Another exogenous state variable in x_t is the duration ρ_z of pesticide protection in days given the current disease pressure for each pesticide z. Starting with the day after application, the protective power of the chemical decreases each day as the interval since application approaches the maximum days of protection. For some chemicals, the duration of protection ρ_z also changes with current PMI values. For example, when PMI is low, sulfur can be applied as infrequently as 21 days. When PMI is high, sulfur can only protect the field for up to 7 days. Table A.2 in Appendix A summarizes recommended application schedules for each chemical category.

Since some chemicals have similar protective power, as well as similar costs, we can group the spray choice into three categories based on the degree of protection they provide for each level of PMI: $a_t = 1$ if chemical categories are sulfur or contact chemicals; $a_t = 2$ if chemical categories are synthetic fungicides (sterol inhibitors, strobilurins, or cell-signaling inhibitors); and $a_t = 3$ for other chemical categories. Thus, the duration ρ_z of pesticide protection in days given the current disease pressure for each pesticide *z* can be either 0, 7, 14, or 21 days, depending on the pesticide applied during the last spray and current weather conditions (PMI).

Table A.3 in Appendix A summarizes evolution of protective power measured in maximum days of protection ρ_z for each PMI-spray combination. Since the duration of protection depends on the chemical sprayed last and PMI_t, we specify the value of ρ_z for each combination of the chemical category of the last spray and PMI_t in the matrix based on Table A.3 in Appendix A. The value of the PMI is the maximum observed value of PMI over the last seven days.

Figure 2 shows the distribution of the interval (in number of days) since the last spray at the time of spray in the data. According to Tables A.2 and A.3 in Appendix A, the recommended spraying intervals based on the chemical last applied and the current level of disease pressure are 7, 14, and 21 days. These recommended intervals are represented by red lines in the figures. The fourth red line is at the 28 day mark. The recommended intervals are generally consistent with what we see in the data, although some growers spray more frequently than 7 days, and others less frequently than 21 days. Fewer than 1% of the growers spray beyond 28 days in any county, and these observations are treated as missing data since they likely represent data errors. For example, a grower may forget to record a spray, or make a mistake when recording the name of the field, and the spray may get assigned incorrectly in the PUR data.

Our data suggests that growers sometimes stretch intervals beyond the recommended reapplication date ρ_z. This can be due to approaching harvest, type of grapes (raisin and wine grape growers can stop powdery mildew management once the berries reach a particular sugar content), and negligible disease pressure. Nevertheless, only 2–4% of total sprays occur at intervals over 21 days, which is the maximum duration of protection of any chemical under the lowest degree of disease pressure according to the University of California Integrated Pest Management (UC IPM) guidelines (see Table A.2 in Appendix A for more details).

We assume that the expected per acre crop value PY_t stays constant throughout the year for each grower, and therefore that growers have perfect foresight regarding the expected revenue per acre for a particular year. Given that many wine and raisin grape growers sell their grapes under pre-determined contracts (Fuller, Alston and Sambucci, 2014), this assumption is not unrealistic. The value of the crop is based on the grape varieties grown, their annual price per ton and per acre yields. Since only limited data on the acreage of specific varieties grown by each grower is available, this variable is set to equal the average revenue per acre for each county for a specific year, based on the data from NASS/USDA Crush Reports (USDA/NASS 2008–2011).

The value of PY_t for each grower is calculated using the region-specific average yield and price for that year. There are six major grape growing regions in California, and the data used in this paper include growers from four of those regions. Sambucci (2015) details the bearing acreage by category of grapes grown, average price per ton of grapes, and total value of production for each of the regions. The North Coast region, which in our sample includes growers from Napa, Sonoma and Mendocino counties, is the region of highest value grapes, but the value of the crop varies among the counties within the region, with Napa being by far the highest value county. The Central Coast region is an area of medium-value grapes, known for its Chardonnay. Chardonnay is a variety that is quite susceptible to powdery mildew infections.

Growers in the Northern Central Valley region grow medium to low value wine grapes, and growers in the Southern Central Valley region grower low value wine grapes, but mostly raisin or table grapes. Of the two counties in the data in the Southern Central Valley region, Fresno has the most raisin growers.

Figure A.1 in Appendix A describes the ten top most popular wine grape varieties by region (share of bearing acreage). These ten varieties account for between 76 and 95 percent of total winegrape acreage in each region. The top varieties are similar among the wine regions, except for the Southern Central Valley region (Fresno and Madera counties in our sample). The most popular wine grape variety in the Southern Central Valley region is French Colombard, which is grown mainly for juice or low cost wine blends. In addition, raisin and table grape acreage in the South Central Valley region is about one and a half times larger than wine grape acreage, so the wine grape industry is not the dominant grape production category. Of the varieties listed, Chardonnay is frequently regarded as the most susceptible to powdery mildew, with Merlot, French Colombard, Petite Sirah, and Rubired having low susceptibility. The rest of the varieties are considered to be moderately susceptible to powdery mildew infections.

From Figure A.1 in Appendix A, it is evident that while most varieties are considered to be moderately susceptible, Chardonnay, a highly susceptible variety, constitutes at least twenty percent of bearing acreage in all regions except the Southern Central Valley. In the Southern Central Valley region, the top two winegrape varieties are considered to have low susceptibility to powdery mildew. However, Chardonnay is still the third most common wine grape variety in this region. Acreage by variety is not observed in the data, and the structural model includes a measure of susceptibility to a powdery mildew outbreak as a source of unobserved heterogeneity. Growers with varieties that are more susceptible to a powdery mildew outbreak are expected to treat powdery mildew more aggressively (using more frequent sprays or spraying with more potent fungicides) than growers with varieties that are less susceptible.

Figure A.2 in Appendix A shows the average annual revenue per acre for each county. We assume that growers have perfect foresight as to what their per acre revenue going to be in a particular year. Many wine growers, especially in high and medium value growing regions, sell their grapes under contract, so the assumption that they have a very good idea of what their revenues will be for the current year is not unrealistic. The same is the case for raisin grape growers.

For spraying costs, we use the average spraying cost for each chemical category. Costs are based on recent UCCE Cost and Return Studies (UCCE 2003-2013) and discussed in more detail in Sambucci (2015). Table A.4 in Appendix A shows the average per acre spraying costs for major chemical categories. Table A.5 in Appendix A shows the variation in spraying costs by region. Annual variation in pesticide or application costs, especially unexpected years of high or low prices would potentially be of interest, but reliable data on application costs by year is not available. Instead, we simply discount the present costs using index of prices paid by growers, but this procedure does not allow enough precision to examine years of unusually high or low pesticide application costs.

Table 1 presents a summary of all action and state variables in the dataset.

5. Results

5.1. Model Selection and Results by County

We estimate several different utility functions which allow for varying degrees of risk aversion: linear utility, logarithmic utility, square root utility, utility with PMI squared, and CRRA utility. Linear utility assumes risk neutrality, logarithmic and square root utilities assume some degree of risk aversion, and CRRA utility allows variation in the degree of risk aversion among the different groups of growers in the sample. Characterizing the risk preferences of growers can help one understand some of the decisions growers make when faced with potential losses from a disease outbreak.

In order to determine the utility function that has the best fit for the data, five different utility functions with and without unobserved heterogeneity were estimated and tested for goodness of fit: linear utility, logarithmic utility, square root utility, utility with PMI squared, and

CRRA utility.[6] Likelihood ratio tests were used to compare CRRA and logarithmic utility, and linear utility with utility with PMI squared to determine which utility functions fits data the best. Likelihood ratio tests were also used for each utility function to test between the model with and without unobserved heterogeneity. Based on the results of the likelihood ratio tests, the CRRA utility function with unobserved heterogeneity was selected as the best fit. Results of the likelihood ratio tests are included in Appendix B.

We use our dynamic structural model to examine the role of the PMI disease pressure forecast in the spraying decisions of the growers. The coefficient on the category of the PMI is therefore a primary parameter of interest. Growers who use powdery mildew pressure forecasting and spray at more flexible intervals are expected to have a larger coefficient on the PMI, while growers who spray at fixed calendar schedules and do not adjust their intervals based on the values of the PMI may have a smaller or insignificant coefficient. Given the structure of the data, the sign of the coefficient on the PMI may be either negative or positive. Many growers adhere to a calendar schedule for applying pesticides to control powdery mildew. Since the value of the PMI varies daily and the sprays may be scheduled in advance, we can observe sprays both during periods of low values of the PMI and during periods of high values of the PMI. If scheduled sprays happen to fall mostly during periods with low values of the PMI, we would observe a negative coefficient on the PMI. On the other hand, if the scheduled sprays fall mostly during periods with high values of the PMI, we would observe a positive coefficient on the PMI. At the other extreme, if a grower did not use a calendar spraying schedule at all and instead sprayed only in response to the PMI, the coefficient on the PMI would also be positive. We expect that even with the use of the PMI, most growers would still retain a calendar spraying schedule, but also use the PMI to adjust the timing of their sprays. Therefore, the sign of the coefficient on the value of the PMI depends to some extent on the degree to which a particular grower follows a calendar spraying schedule. In addition, we expect the coefficient on the value of the PMI to increase with the use of the PMI, assuming that the growers become more responsive to the forecasted powdery mildew pressure.

We expect the coefficient on susceptibility and the value of the susceptible proportion P_v to vary by region. If the sample of growers is representative of grape growers in each region, we would expect to see higher values of coefficient on susceptibility and the values of susceptible

[6] We estimate and test the different utility functions using Model 1, as likelihood ratio tests show that Model 2 does not provide significant improvement over Model 1 in the ability of the model to fit the data.

proportion P_v in the Central and North Coast regions. Chardonnay is the most popular variety in the Central Coast region and this is also the region that usually experiences high powdery mildew pressure because of its mild climate and proximity to the coast. Growers in North Coast grow especially high value grapes, including white grape varieties that are more susceptible to powdery mildew infections.

We first estimate the CRRA utility with and without unobserved heterogeneity for wine and raisin grape growers by county. Table 2 presents the parameter estimates for CRRA utility with and without unobserved heterogeneity for Model 1 ($\beta = 0.9$). These estimates include data for all available years, and use average values of per acre revenue and application costs for each chemical category for all years. The estimates are listed for each county separately and grouped by grape growing region, since regions are similar in grape value, categories of grapes grown, and market conditions.

We also conduct a likelihood ratio test between the model with unobserved heterogeneity and the model without unobserved heterogeneity. The model without unobserved heterogeneity is a special case of (and therefore a constrained version with fewer parameters than) the model with unobserved heterogeneity. The test statistic D is given by:

$$D = 2L^a - 2L^o , \tag{22}$$

where L^a is the log likelihood of the model with unobserved heterogeneity and L^o is the log likelihood of the model without unobserved heterogeneity. The test statistic D is distributed chi-squared with 1 degree of freedom (since the number of parameters in the model with unobserved heterogeneity minus the number of parameters in the model without unobserved heterogeneity = 1 degree of freedom). If the test statistic D is greater than the critical value 0.0039, then the coefficient on unobserved heterogeneity is statistically significant at a 5% level and the model with unobserved heterogeneity produces a statistically significant improvement in the ability of the model to fit data.

According to the likelihood ratio tests in the last column of Table 2, CRRA utility with unobserved heterogeneity produces a significant improvement in the value of the log likelihood. We therefore focus our discussion on the results of the CRRA utility with unobserved heterogeneity.

The coefficients on the PMI are positive and significant in Table 2 for all counties except Napa and Madera. The magnitude of the coefficients varies between about 0.7 and 27, which means that an increase in the maximum value of the Powdery Mildew Index over the past 7 days from low to medium or from medium to high increases the expected crop value loss $c(x_t, \nu, \theta)$ from powdery mildew by $0.70 in Madera county to $4.82 in Mendocino County (in 2008 US dollars) per acre per day (or, by $171 to $1,180 per acre per year). The expected loss of crop value $c(x_t, \nu, \theta)$ incorporates the probability of an outbreak as well as the net loss (salvage value minus crop loss) in the case of an outbreak. Differences in the magnitude of coefficients are due to large differences in revenue per acre, as shown in Figure A.2 in Appendix A.

The coefficient on i_t / ρ_{tz} ranges from 0.23 to 0.93, which means that an increase in the ratio of the interval i_t since last spray over the recommended maximum days of pesticide protection ρ_Z from 0 (the grower just sprayed) to 1 (the grower has reached the maximum days of protection) increases the expected crop value loss $c(x_t, \nu, \theta)$ from powdery mildew in the case of an outbreak by $0.23 to $0.93 (in 2008 US dollars) per acre per day, or between $56 and $228 per acre per year.

The coefficient on unobserved susceptibility to powdery mildew ranges between about 1 and 24, which means that being susceptible to powdery mildew increases the expected crop value loss $c(x_t, \nu, \theta)$ from powdery mildew in the case of an outbreak, by $1 to $24 (in 2008 US dollars) per acre per day ($245 to $5,880 per acre per year). The estimated share of plots with varieties susceptible to powdery mildew is very low for most counties (below 1%), but is very high in Napa and Sonoma (97%).

The value of γ, the coefficient of relative risk aversion, is estimated to be between 0.4 (raisin grape growers) and 1.4 (wine grape growers in San Joaquin). Estimates of γ are lower for raisin grape growers than wine grape growers, and γ also varies less among raisin grape growers in different counties. Estimates of the coefficient of relative risk aversion for raisin grape growers fall between 0.42 and 0.44 for raisin grape growers. The coefficient of relative risk aversion for wine grape growers falls between 0.67 and 1.40, with the highest value of the coefficient for growers in San Joaquin county. Wine grape growers in lower value counties of Madera and Fresno have a similar estimated coefficient of relative risk aversion as wine grape growers in Napa or Sonoma, which is where the grapes of the highest value are grown. On the other hand, estimates for growers in Mendocino, also a county with high-value grapes, have a similar estimated coefficient of relative risk aversion as growers in San Joaquin or San Luis Obispo, which are counties with low- or medium-value grapes.

Table 3 presents the parameter estimates for CRRA utility with unobserved heterogeneity for Model 2 ($\beta = 0.9996$). Results from Model 2 in Table 3 show that the coefficient on the PMI is negative and significant for all counties. The coefficient on i_t / ρ_{tz} varies between 0.26 for growers of raisin grapes in Fresno and 4.36 for growers of raisin grapes in Napa. The coefficient on the indicator of perceived susceptibility to powdery mildew varies between 0.08 and 4.521. The coefficient of relative risk aversion is around 0.7 for all counties. The main difference between estimates for Model 1 (Table 2) and Model 2 (Table 3) is the negative coefficient on the PMI in the latter. The possible reasons for the negative sign on the coefficient of the PMI are discussed above. Since a negative coefficient on the PMI represents both the effect of calendar schedule and the response to the disease pressure, the interpretation of the coefficient on the PMI is best done as a comparison between growers who use the PMI and those who do not, which we conduct below. In addition, while the coefficients on the PMI are negative for all counties, coefficients on i_t / ρ_{tz} and unobserved susceptibility vary over a greater range of values than in Model 1.

We conduct likelihood ratio tests between the more myopic Model 1 ($\beta = 0.9$) and the more dynamic Model 2 ($\beta = 0.9996$). The myopic model is a special case of the dynamic model. The test statistic D is given by Equation (22), where L^a is now the log likelihood of the more dynamic model and L^o is now the log likelihood of the more myopic model. The test statistic *D* is distributed chi-squared with 1 degree of freedom. If the test statistic *D* is greater than the critical value 0.0039, then the more dynamic model produces a statistically significant improvement in the ability of the model to fit data at a 5% level.

Table 4 presents the results of the likelihood ratio tests that compare the goodness of fit between Model 1 ($\beta = 0.9$) and Model 2 ($\beta = 0.9996$). The likelihood ratio tests in Table 4 indicate that Model 2 provides significant improvement in the fit to the data for only two out of ten counties: growers of wine grapes in Napa and Fresno. For other counties, using the daily discount factor of $\beta = 0.9996$ instead of $\beta = 0.9$ does not provide significant improvement in the ability of the model to fit the data. We therefore focus primarily on the results of Model 1 ($\beta = 0.9$) for all counties, while also discussing the results of Model 2 ($\beta = 0.9996$) for wine grape growers in Napa and Fresno. It is possible that a different daily discount factor that falls between these two values could result in a better fit.

As a robustness check, Table A.6 in Appendix A presents results that only use data for plots with weather stations within a distance that can be considered 'close'.[7] The estimates restricted to weather stations in the close range are likely to provide more precise coefficient estimates, but they also reduce the amount of usable data and the rest of the estimates continue using data from all weather stations, with the mean distance between the plot and the closest weather station of about 10 miles. The results suggest that growers in all counties make some adjustments to the timing of their sprays based on the PMI, except in Napa, where the coefficient on the PMI is negative and not significant. The coefficient on susceptibility and the value of susceptible proportion P_v is low in Central Coast, where we would expect it to be higher due to the climate and large proportion of Chardonnay. However, since we do not observe the varieties planted by the growers in our sample, it is possible that growers in this dataset are not representative of the regional sample.

Because the results of likelihood ratio tests show that CRRA utility provides the best fit to the data, we use the CRRA utility to examine the variation in the degree of risk aversion among different groups of growers, under various degrees of disease risk, and for years of different revenue levels.

5.2. PMI Users vs. Non-Users

In the next set of results, we estimate and compare parameters for users and non-users of the PMI separately to determine if there is a difference in how these growers respond to disease pressure risk. The availability of the PMI serves a proxy for the use of the PMI (which is endogenous). The survey data include information on when PMI first became available to the growers, which is exogenous, rather than when the grower started using the PMI (endogenous). Table 5 presents the results of CRRA utility estimates for growers pre- and post- PMI receipt. If

[7] North Coast counties Napa and Sonoma are especially subject to microclimates and require strictest range limitations: 'too far' is >5 miles (8 km) and 'close' is <3 miles (5 km). Mendocino: 'too far' is >10 miles (15 km) and 'close' is <5 miles (8 km). San Luis Obispo is where most of our Central Coast observations are: 'too far' is >15 miles (23 km) and 'close' is <8 miles (13 km). Valley counties are generally flat and more uniform in climate. In Fresno and Madera, 'too far' is >37 miles (60 km) and 'close' is <23 miles (38 km). In San Joaquin, 'too far' is >18 miles (30 km) and 'close' is <7.5 miles (12 km). Distance ranges are from Lybbert, Magnan and Gubler (2016). Conversions from kilometers to miles are rounded to the closest half-mile.

the growers rely on the PMI more post-receipt, we would expect to see a larger coefficient on the PMI post-receipt than prior to the receipt of the PMI.

In addition, we would expect an increase in the magnitude and significance of coefficient on the indicator of current field protection (i_t/ρ_{tz}) post-receipt. This is because the values of ρ_{tz} (days of protection from the chemical applied during the previous spray) are based on the current values of the PMI: as the value of the PMI increases, the days of protection allowed by the last spray chemical fall, as described in Table A.3 in Appendix A. So, growers would be more likely to spray in response to changes in value of i_t/ρ_{tz} if they monitor the PMI than they would be from assuming ρ_{tz} to be an average fixed number for each chemical category, since in the latter case the grower would not realize that i_t/ρ_{tz} had changed.

According to the results in Table 5 (Model 1), the coefficients on the PMI increase for wine grape growers in Madera, Mendocino, and Sonoma after the PMI becomes available. The coefficient on the value of the PMI increases from 0.32 to 0.75 in Madera, 4.79 to 4.81 in Mendocino, and from -0.26 to 1.75 in Sonoma. The coefficients can be interpreted as the change in the expected crop value loss $c(x_t, v, \theta)$ from powdery mildew, which incorporates the probability of an outbreak as well as the net loss (salvage value minus crop loss) in the case of an outbreak, in 2008 US dollars per acre per day. This means that for growers in Madera an increase in the maximum value of the Powdery Mildew Index over the past 7 days from low to medium or from medium to high increases the expected loss from powdery mildew from \$0.32 to \$0.75 per acre per day after they begin using the PMI. Similarly, prior to the receipt of the PMI, an increase in the maximum value of the PMI over the preceding 7 days from low to medium or from medium to high, did not increase the expected loss from powdery mildew (the coefficient on the PMI was negative and not significant). After the growers began using the PMI, the expected loss from powdery mildew from increase in the PMI changed to \$1.75 per acre. Estimates for growers in other counties show slightly smaller coefficients on PMI post-receipt. In the case of Napa, the coefficient on the PMI becomes negative and insignificant.

At the same time, wine grape growers in Fresno, Madera, Napa and Sonoma also have larger coefficients on the value of i_t/ρ_{tz} after receiving the PMI. In Fresno, the coefficient on i_t/ρ_{tz} changed from 0.24 to 1.27, in Madera—from 0.28 to 0.44, in Napa—from 0.03 to 0.93 and in Sonoma—from 0.93 to 4.46. As discussed above, this result can be interpreted as an increase in the expected loss of crop value from powdery mildew (in 2008 US dollars) per acre per day, as the ratio of the interval i_t since last spray over the recommended maximum days of protection ρ_Z increases from 0 to 1.

In addition, the coefficient on the perceived susceptibility of the variety grown decreases for growers in Napa and Sonoma with receipt of the PMI. For growers in Napa, the coefficient on varietal susceptibility decreases from 14.73 to 9.52 and for Sonoma—from 23.42 to 4.96. The coefficient on varietal susceptibility also decreases for raisin grape growers in Tulare (from 4.99 to 2.23). The coefficient on varietal susceptibility increases for wine grape growers in Fresno in Madera, and stays the same for growers in all other counties. These changes suggest that, in most counties, growers become more responsive to the values of the PMI post-receipt (since an increase in the PMI increases the expected loss from powdery mildew if the grower does not spray, and, therefore, increases the probability of spraying for each category of spray), either by spraying more frequently in response to large values of PMI, or by timing their sprays according to the protection provided by the last sprayed chemical, which also changes based on the values of the PMI. However, this result does not hold for all counties – there are almost no changes in coefficients between the users and non-users of the PMI for wine grape growers in San Joaquin and San Luis Obispo, and raisin grape growers in Madera. The expected crop loss from powdery mildew decreases with increase in the PMI or i_t/ρ_{tz} for raisin grape growers in Tulare.

Estimates of coefficient of relative risk aversion are similar for the two groups of growers (users and non-users of the PMI) for all counties except Sonoma, where users of the PMI exhibit much higher relative risk aversion than non-users (1.47 for users compared to 0.49 for non-users). This finding suggests that the group of growers who use the PMI in Sonoma includes growers with higher levels of relative risk aversion than non-users, but this trend is not present in any of the other counties.

Results from Model 2 are presented in Table A.7 in Appendix A. While the coefficients on the PMI are still negative, they increase with the use of the PMI for all counties except Fresno and Napa, which is consistent with the results for Model 1 in Table 5. The coefficients on i_t/ρ_{tz} increase or stay the same for all counties except raisin growers in Fresno and Tulare. The coefficient on the susceptibility to powdery mildew outbreaks varies between 0.1 and 3.7 for users of the PMI and between 0.1 and 4.5 for non-users. The coefficient of relative risk aversion is still about 0.7 for all growers.

5.3. Years of Low, Medium, and High Powdery Mildew Pressure

It may be possible that the decrease in the coefficient on susceptibility may indicate that growers are more confident in their powdery mildew management strategy and time their sprays according to the forecasted disease pressure more than the perceived susceptibility of a particular plot. To examine the response of the growers to various levels of disease pressure risk, we estimate the model for years of low/medium or high powdery mildew pressure. The results for Model 1 ($\beta = 0.9$) are reported in Table A.8 in Appendix A.[8] The years are grouped by average observations of the PMI index for all three categories (low, medium, and high) for each year, by county. Figure 1 presents the details on the distribution of the PMI observed in the data.

Among wine grape growers, the largest changes in the coefficients on the PMI and i_t/ρ_{tz} between years of low and high powdery mildew pressure are in Fresno, Napa and Sonoma counties. In Fresno, the coefficient on the value of the PMI is 0.93 in years of low powdery mildew pressure and 1.46 in years of high powdery mildew pressure. This implies that the expected loss from powdery mildew with an increase in the observed category of the PMI by 1 (from low to medium, or from medium to high) differs by \$0.53 per acre per day between years of low and high powdery mildew pressure. Similarly, the coefficient on i_t/ρ_{tz} increases from 0.12 to 0.19. For growers in Napa, the coefficient on the PMI is negative or not significant in years of low and medium powdery mildew pressure, and increases to 2.05 in years of high powdery mildew pressure. The coefficient on i_t/ρ_{tz}, on the other hand, decreases from 2.57 in years of low powdery mildew pressure to 0.45 in years of high powdery mildew pressure. The coefficient on varietal susceptibility also decreases from about 15 in years of low and medium powdery mildew pressure to 5.5 in years of high powdery mildew pressure. In Sonoma, the coefficient on the category of the PMI is large in years of low powdery mildew pressure, small and not significant in years of medium powdery mildew pressure and increases again to 7.6 in years of high powdery mildew pressure. The coefficient on i_t/ρ_{tz} increases from 0.41 in years of medium powdery mildew pressure to 9.27 in years of high powdery mildew pressure. Estimates for growers in Sonoma also show a larger coefficient of risk aversion in years with higher disease pressure. The differences in

[8] These and subsequent results are reported for Model 1 only, as Model 2 generally does not provide significant improvement over Model 1 in the ability of the model to fit the data.

the estimated coefficient of relative risk aversion are likely due to the slight differences in the plots observed in the data among the low, medium, and high-pressure years. Given the findings in Table A.8 in Appendix A, it is possible that the sample of plots active in the years with relatively high powdery mildew pressure include a large share of PMI users. Estimates for grape growers in San Joaquin, San Luis Obispo, and Mendocino vary very little among the three groups of years. For wine grape growers in Madera, the coefficient on the PMI becomes positive and significant in years of high powdery mildew pressure, while the coefficient on i_t/ρ_{tz} decreases in value. Among raisin grape growers, the coefficients for both PMI and i_t/ρ_{tz} increase for growers in Madera and Tulare, and growers in Fresno show a decrease in coefficient on the PMI, but a large increase in the coefficient on i_t/ρ_{tz}.

Tables A.9 and A.10 in Appendix A provide the comparison between growers who use and do not use the PMI, respectively, for years of varying powdery mildew pressure. In most cases, growers who use the PMI become more responsive to disease pressure risk (as indicated by the increase in the expected crop loss from increase in the value of the PMI). Differences between growers who receive the PMI and those who do not receive the PMI vary by county. Coefficients on the PMI for growers of wine grapes in Madera are negative and significant in some cases, which may indicate that they tend to spray based on calendar schedule, which does not always correspond to disease risk based on weather. However, the coefficients on on i_t/ρ_{tz} are larger for growers in Madera with the use of the PMI, which indicates that while they do not necessarily spray in response to high levels of PMI (since an increase in the value of the PMI does not increase the expected crop loss from powdery mildew), the increase in the expected loss of crop value from an increase in the PMI results from changes in the degree of protection due to changes in disease pressure. In other parts of the Central Valley and in the North Coast counties, the response to PMI between users and non-users appears to be very similar, suggesting that the variation in weather (which drives powdery mildew risk) increases the perceived probability of the expected loss from powdery mildew regardless whether or not the growers use the official index. Among raisin grape growers, the value of the expected loss function is higher among the users of the PMI in years of low and high disease pressure, but the coefficients on the value of the PMI and i_t/ρ_{tz} are very similar in years of medium disease pressure.

5.4. Years of Low, Medium, and High Revenue Per Acre

Next we examine the response of growers to disease risk during years of different per acre revenue. We group the years of revenue by low, medium, and high per acre revenue, using a 20 percent deviation from the mean per acre revenue to define the categories. Table A.11 in Appendix A includes the results. The coefficients on the PMI and i_t/ρ_{tz} increase for wine grape growers in Madera, Napa, Sonoma, and San Luis Obispo in years of high revenue per acre. Coefficients on these variables do not change, or change in the opposite direction for wine grape growers in Fresno and Mendocino. The value of the expected loss of crop value increases between low and high revenue loss for raisin grape growers in Madera, Fresno and Tulare.

Tables A.12 and A.13 in Appendix A present results for users and non-users of the PMI separately. The years of low, medium, and high revenue per acre are not distributed evenly among the counties in each region, so the estimates in Tables A.12 and A.13 in Appendix A report results by region rather than county. Since prior tables demonstrate the differences among counties within the region as well as among the regions, the results by region offer less precision. The main and obvious difference between users and non-users of the PMI grouped by year of high, medium and low revenue is that growers who do not report receiving the PMI in several cases show negative and significant coefficients on the PMI. Growers who report receiving the PMI show insignificant or positive coefficients on the PMI, which, in all cases, increase for years of high revenue per acre.

6. Counterfactual Simulations

We use the results of our dynamic structural econometric model to run counterfactual simulations to calculate the value to growers of the PMI. In particular, we use the parameter estimates to simulate what would happen if all growers received the PMI, and also to simulate what would happen if no growers received the PMI, and then compare the average grower welfare under the two counterfactual scenarios as a measure of the value to the growers of the PMI.

To calculate and compare the welfare of receiving versus not receiving the PMI, we simulate what would happen if all growers (PMI users and non-users alike) received the PMI, and compare that to what would happen if no growers received the PMI. Because those who received the PMI may be a select sample, we cannot simply compare the welfare of the users of the PMI with those of non-users, but instead simulate the counterfactual of all growers receiving the PMI versus the counterfactual of no growers receiving the PMI.

For each county, grape type, and year combination in the data set, we simulate 100 possible trajectories for spraying decisions a_t for each grower over $T = 245$ days, using the actual values for PMI_t and PY_t and the parameter values that are significant at a 5% level from our results for PMI users for that respective county in Table 5. We then simulate 100 possible trajectories for spraying decisions a_t for each grower over $T = 245$ days using the actual values for PMI_t and PY_t and the parameter values that are significant at a 5% level from our results for PMI non-users for that respective county in Table 5. We compare the average grower welfare if everyone used PMI (averaged over 100 simulations) with the average grower welfare if no one used PMI (averaged over 100 simulations), for each county and category of grapes combination. The results for Model 1 are presented in Table 6; the results for Model 2 (which are based on parameter estimates from Table A.7 in Appendix A) are presented in Table 7.

According to the results for Model 1 in Table 6, average welfare is lower with the PMI disease forecast information for growers of wine grapes in Madera and Sonoma counties and is the same with and without the PMI disease forecast information for growers of wine grapes in all other counties except Fresno. Average welfare is higher with the use of the PMI disease forecast information for wine grape growers in Fresno. Also, welfare is higher with the use of PMI for growers of raisin grapes in all counties. According to the results for Model 2, which produces a statistically significant improvement in the ability of the model to fit data for growers of wine grapes in Fresno and Napa, in Table 7, average welfare is higher with the use of the PMI disease forecast information for wine grape growers in Fresno but lower with the use of PMI disease forecast information for wine grape growers in Napa.

7. Conclusion

This paper estimates a dynamic structural econometric model of the decision of grape growers of whether and when to spray their crop. We compare the parameters among different counties; between users and non-users of PMI disease forecast information; for years of low, medium, and high powdery mildew pressure; and for years of high, medium or high value of per acre revenue. In addition, we estimate the distribution and effects of unobserved varietal susceptibility, which is hypothesized to contribute to the spraying decisions by the growers.

We estimate two versions of the model. Model 1 is a more myopic scenario, which uses a daily discount factor of 0.9. Model 2 is a more dynamic scenario and uses a daily discount factor of 0.9996. Likelihood ratio tests between the two models suggest that, with the exception of wine grape growers in Napa and Freso, Model 2 does not provide significant improvement over Model 1 in the ability of the model to fit the data. We therefore focus primarily on Model 1 for all counties, while also discussing the results of Model 2 for wine grape growers in Napa and Fresno. Both models model the decision-making process as dynamic and vary only in the degree to which the future payoffs factor into the present decision-making. It is possible that a discount factor between the two values tested in this paper would provide a better fit.

The results suggest that, while all growers use weather for guidance when planning the applications of pesticides to manage powdery mildew, growers who use the PMI are more responsive to current disease pressure than growers who do not, but these results vary among counties. Increases in the value of the PMI increase the expected crop loss for each level of disease pressure and for each level of protection provided by the pesticide product currently on the field.

When the data are grouped by years of low, medium, or high powdery mildew pressure, the function of expected loss in crop value due from an outbreak of powdery mildew increases for growers in several counties in years of high powdery mildew pressure. The value of the expected loss function increases in years of high powdery milder pressure for growers of wine grapes in Fresno, Madera, Napa, and Sonoma. Estimates for growers of wine grapes in San Joaquin, Mendocino, and San Luis Obispo are very similar among the three groups of years grouped by powdery mildew pressure. The value of the expected loss function increases for raisin grape growers in Fresno and Tulare, and decreases for raisin grape growers in Madera.

When growers are grouped based on the use of the PMI, the results are similar: in San Joaquin, Mendocino, and San Luis Obispo the results for users and non-users of the PMI are very similar and do not vary based on powdery mildew pressure for the group of years. Wine grape growers in Sonoma show the largest differences both between users and non-users of PMI and among years of low, medium, or high powdery mildew pressure. The expected loss of crop value for users of the PMI in Sonoma is higher compared to the non-users for each group of years. Wine grape growers in Madera and Napa show responses similar to wine grape growers in Sonoma, but with fewer differences among groups of years with low, medium, or high powdery mildew pressure. Among raisin grape growers, the value of the expected loss function is higher for users of the PMI are among all counties, and higher for all growers in years with high powdery mildew pressure.

Coefficients on the PMI and on i_t/ρ_{tz} (the ratio of the days since last spray to the maximum days of protection provided by the chemical applied on the plot during the last spray) increase for wine grape growers in Madera, Napa, and Sonoma and raisin growers in Tulare in years where the revenue per acre is higher than average. Coefficients on the PMI and i_t/ρ_{tz} decrease or stay the same for growers of wine grapes in Fresno or Mendocino between years of high and low revenue per acre.

Differences between users and non-users of the PMI in the results grouped by years of low, medium, or high revenue per acre are less clear. The main and obvious difference between users and non-users of PMI grouped by year of high, medium, and low revenue is that the coefficient on the PMI in the expected loss function is negative and significant for several groups of growers who do not report receiving the PMI. Growers who report receiving the PMI show insignificant or positive coefficients on PMI, which, in all cases, are higher in years of high per acre revenue.

The value of the coefficient of relative risk aversion γ is between 0.4 (raisin grape growers) and 1.4 (wine grape growers in San Joaquin and Sonoma). Raisin grape growers in this sample have lower relative risk aversion than wine grape growers, and also less variation in the coefficient of relative risk aversion among growers in different counties. Estimates of the coefficient of relative risk aversion for raisin grape growers fall between 0.42 and 0.44. The coefficient of relative risk aversion for wine grape growers falls between 0.49 and 1.47, with the highest value of the coefficient for growers in Sonoma county. So far it is unclear whether coefficient of relative risk aversion for wine grape growers varies with any particular location or crop value. Wine grape growers in lower value counties of Madera and Fresno have a similar estimated coefficient of relative risk aversion as wine grape growers in Napa, which is where the grapes of the highest value are grown. On the other hand, estimates for growers in Sonoma, also a county with very high-value grapes, have a similar estimated coefficient of relative risk aversion as growers in San Joaquin or San Luis Obispo, which are counties with low- or medium-value grapes. Estimates of coefficient of relative risk aversion are similar for users and non-users of PMI for all counties except Sonoma, where users of PMI exhibit much higher relative risk aversion than non-users (1.47 for users compared to 0.49 for non-users). This finding suggests that the group of PMI users in Sonoma includes growers with higher levels of relative risk aversion than non-users, but this trend is not present in any of the other counties. The coefficient of relative risk aversion varies very little among the counties in Model 2 and is around 0.7 for all growers.

The coefficient on unobserved susceptibility to powdery mildew ranges between about 0.033 and 23.41 in Model 1, and between 0.23 and 4.52 in Model 2, which means that being susceptible to powdery mildew increases the expected crop value loss $c(x_t, \nu, \theta)$ from powdery mildew, which incorporates the probability of an outbreak as well as the net loss (salvage value minus crop loss) in the case of an outbreak, by \$0.03 to \$23.41 (in 2008 US dollars) per acre per day (Model 1), or by \$0.23 to \$4.52 (Model 2). The estimated share of plots with susceptible varieties ranges from below 1% to as high as 99% (in Napa, using Model 1). The large share of varieties that growers perceive as susceptible to a powdery mildew infection in Napa is not surprising – wine grapes in Napa are some of the most valuable in the world (both in value per ton and in revenue per acre), and Chardonnay is the second most planted variety in that region.

Finally, the effects of having the PMI disease forecast information on the average welfare of the growers also vary by region. Fresno is the only county where having the PMI disease forecast information increases average welfare for wine grape growers. Having the PMI disease forecast information decreases average welfare for wine grape growers in Sonoma, Madera, and Napa, and has no effect on average welfare for wine grape growers in the other counties. On the other hand, having the PMI disease forecast information increases average welfare for raisin grape growers in all counties.

Wine grapes in Fresno, as well as raisin grapes in Fresno, Madera and Tulare, are of lower value than grapes in all other counties, except wine grapes in Madera. Because the costs of spraying are larger relative to potential crop revenue for the growers in these counties, growers in these counties would be more likely to care about using the PMI disease forecast information to avoid unnecessary sprays. In contrast, for growers in counties with grapes of higher value, the costs of spraying are a smaller share of revenue per acre. In this case, growers would care more about eliminating any damage to the crop from a potential outbreak of powdery mildew, and would be willing to apply extra sprays to provide a higher level of protection. Consequently, having the PMI disease forecast information may not increase the average welfare of these growers. These results are consistent with reduced form econometric results from Lybbert, Magnan and Gubler (2016), who find that growers of grapes of higher value are more likely to over-apply pesticides in response to high levels of forecasted disease pressure. Results for growers of wine grapes in Madera are the only ones that do not fit this scenario: wine grapes in Madera are of low value, and yet the welfare of the growers declines with the use of the PMI disease forecast information. Since the estimates in this paper use a fairly small sample of growers, it is possible that these results are due to the growers in the sample not being familiar with the use of the PMI disease forecast information. In future work, we hope to expand the sample to provide results that are more representative.

The primary advantage of reduced-form models such as those in Lybbert, Magnan and Gubler (2016) are that one can use continuous variables without having to discretize them and, because state-space constraints are less of a concern, one can include many covariates. However, the reduced-form models only estimate the per-period probability of spraying, and therefore do not have a clear structural interpretation. Because the payoffs from spraying depend on the risk of powdery mildew infection, which varies stochastically over time, a grower who hopes to make a dynamically optimal decision would need to account for the option value to waiting before making an irreversible decision to spray (Dixit and Pindyck 1994). The parameters in reduced-form models are therefore confounded by continuation values.

The dynamic structural model developed in this paper provides several advantages to modeling the spraying decisions of grape growers. Unlike reduced-form models, a structural approach explicitly models the dynamics of spraying decisions and allows the estimation of additional parameters such as the degree of risk aversion exhibited by the growers and the distribution and effects of unobserved susceptibility of varieties to powdery mildew infections.

One main advantage of the structural model is that is that it allows us to estimate the effect of each state variable on the expected payoffs from the decisions to spray or not to spray, while accounting for the continuation value, which is the expected value of the value function next period. Therefore, the estimated parameters have direct economic interpretations.

A second main advantage of the structural model is that the parameter estimates from our structural model can be used simulate counterfactual scenarios. In this paper, we use the parameter estimates to simulate what would happen if all growers received the PMI, and also to simulate what would happen if no growers received the PMI, and then compare the average grower welfare under the two counterfactual scenarios as a measure of the value to the growers of the PMI.

In future work we hope to obtain more data to enable us to allow the parameters to vary among grower groups with different individual characteristics, such as by gender and the level of experience with vineyard management, and also to capture changes over multiple seasons of time.

The parameter estimates can then be used to evaluate how the welfare of growers change over time with the use of the PMI disease forecast information.

In addition, it is worth exploring whether data limitations may be affecting estimates of unobserved varietal susceptibility to powdery mildew infections. It is possible that the varieties grown by the current grower sample are not representative of the general distribution of varietal acreage each county, and estimating this model for a larger dataset may provide more precise estimates of varietal susceptibility. Using data for a larger sample of grape growers would serve to confirm the validity of our results for the larger subset of the grape growing industry.

Our results have important implications for grape powdery mildew management and the provision of disease forecasting information. In addition, the dynamic structural econometric modeling approach we use in our research to analyze the pesticide spraying decisions of grape growers in response to disease forecasting information innovates upon previous methodological approaches to analyzing pest management, and can be applied in many other settings, including to other pests and crop diseases in other areas of the world.

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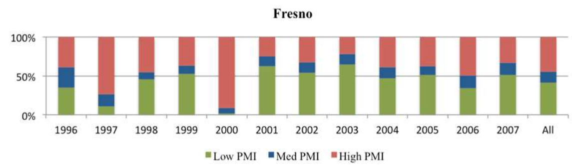
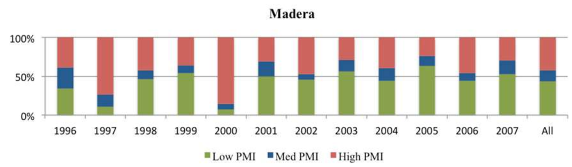
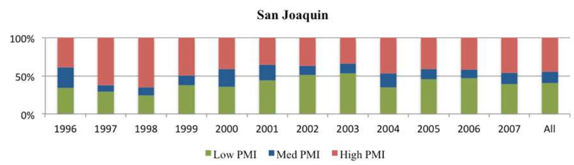
Figure 1: Distribution of Powdery Mildew Pressure by Year and County

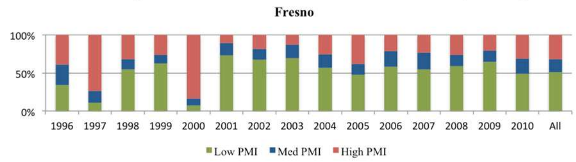
Wine Grape Growers: Central Valley Region

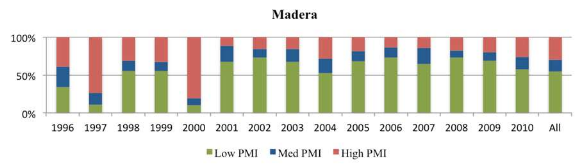


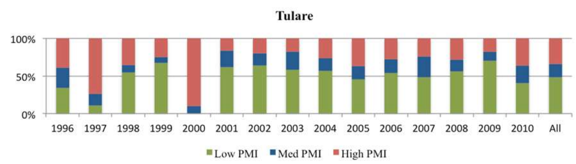




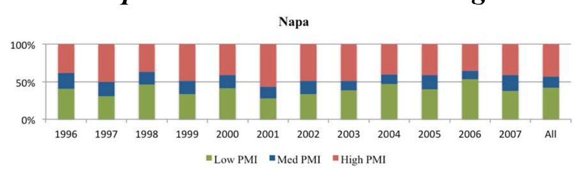
Raisin Grape Growers: Central Valley Region

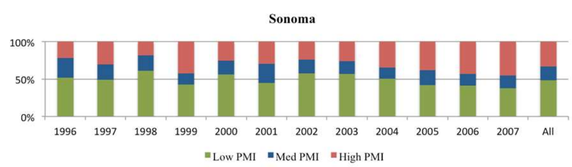


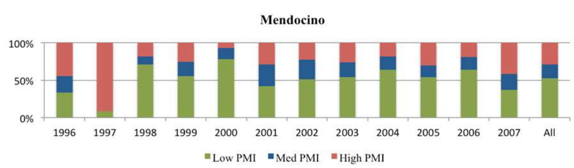




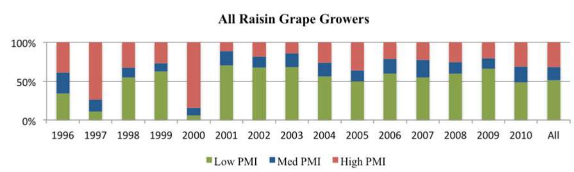
Wine Grape Growers: North Coast Region

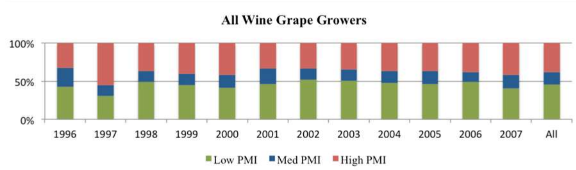






Average Over All Counties





Wine Grape Growers: South Coast Region

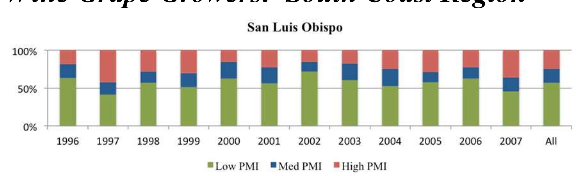
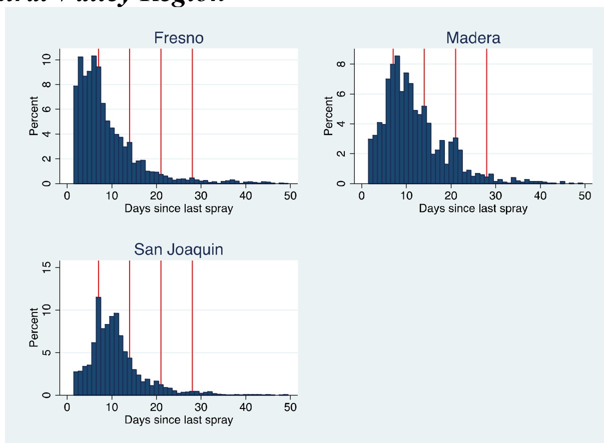
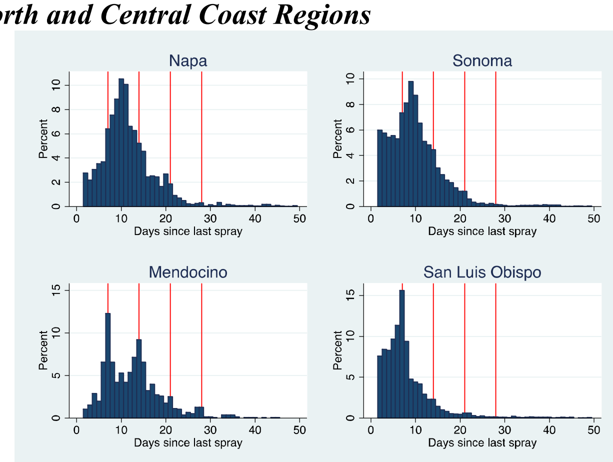


Figure 2: Distribution of Interval Since Last Spray at the Time of Spray

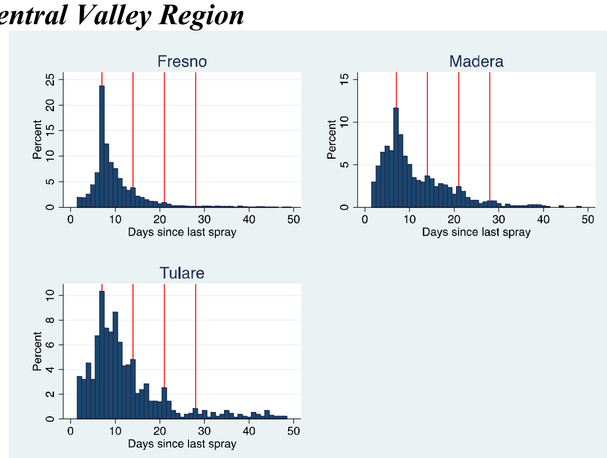
Wine Grape Growers: Central Valley Region



Wine Grape Growers: North and Central Coast Regions



Raisin Grape Growers: Central Valley Region



Notes: Graphs plot the distribution of of the interval (in number of days) since the last spray at the time of spray. According to Tables A.2 and A.3 in Appendix A, the recommended spraying inervals based on the chemical last applied and the current level of disease pressure are 7, 14, and 21 days. These recommended intervals are represented by red lines in the figures. The fourth red line is at the 28 day mark.

Table 1: Summary Statistics

	Number of Sprays				Interval Since Last spray		Average Revenue Per Acre	Average Spraying Cost			Share of PMI by Category		
	Sulfur	Synthetics	Other	Total	Observations	Mean		Sulfur	Synthetic	Other	Low	Med	High
						days	*2008 $ per acre*	*2008 $ per acre*			*percent*		
Wine Grape Growers													
Central Valley													
Fresno	3,556	601	53	4,210	4,914	7.7	2,886	10	46	42	49	16	35
Madera	2,218	119	2	2,339	2,427	11.4	2,886	10	46	42	54	17	29
San Joaquin	3,974	600	16	4,590	4,923	10.8	5,651	10	46	42	49	18	33
North Coast													
Napa	4,157	1,348	75	5,580	5,980	11.7	10,774	31	61	44	42	15	43
Sonoma	8,193	2,163	57	10,413	12,767	9.1	8,852	31	61	44	48	19	33
Mendocino	1,350	403	5	1,758	1,817	13.2	6,979	10	49	41	56	20	25
Central Coast													
San Luis Obispo	5,654	235	62	5,951	7,573	7.0	7,253	10	49	41	58	19	24
Raisin Grape Growers													
Central Valley													
Fresno	11,685	2,225	8	13,918	14,310	9.7	1,597	11	46	42	51	17	32
Madera	1,101	306	-	1,407	1,443	11.6	1,597	11	46	42	54	16	30
Tulare	1,260	798	6	2,064	2,085	11.8	1,597	11	46	42	48	17	34

Note: Revenue per acre and costs of spraying are reported in 2008 US dollars, averaged over all years in the data.

Table 2: Results for CRRA Utility (Model 1: β=0.9)

	With Unobserved Heterogeneity					**Without Unobserved Heterogeneity**			**Likelihood Ratio Test Statistic**
	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion	Coefficient on:		Coefficient of Relative Risk Aversion	
	PMI	i_t / ρ_{tz}	Susceptibility			PMI	i_t / ρ_{tz}		
Wine Grape Growers									
Central Valley									
Fresno	0.704*	0.268*	2.960*	0.590*	0.26	1.754*	0.136*	0.598*	15,380*
	(0.179)	(0.070)	(0.285)	(0.012)		(0.020)	(0.019)	(0.001)	
Madera	-0.874	0.923*	4.010*	0.679*	0.34	-0.532*	0.851*	0.685*	158*
	(0.376)	(0.181)	(0.378)	(0.014)		(0.010)	(0.013)	(0.001)	
San Joaquin	4.181*	0.850*	0.980*	1.400*	0.00	4.177*	0.845*	1.400*	128,972*
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	
North Coast									
Mendocino	4.817*	0.928*	1.000*	1.100*	0.00	4.794*	0.906*	1.400*	49,957*
	(0.000)	(0.000)	0.000	(0.000)		(0.000)	(0.000)	(0.000)	
Napa	-0.482	0.921*	9.924*	0.626*	0.97	3.00*	1.00*	0.600*	2,476*
	(0.571)	(0.147)	(1.059)	(0.007)		(0.000)	(0.000)	(0.000)	
Sonoma	-0.432*	0.405*	24.155*	0.472*	0.97	4.863*	1.531*	0.672*	39,672*
	(0.102)	(0.053)	(0.352)	(0.015)		(0.058)	(0.040)	(0.000)	
Central Coast									
San Luis Obispo	5.849*	0.925*	0.990*	1.100*	0.00	5.836*	0.937*	1.400*	19,162*
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	
Raisin Grape Growers									
Central Valley									
Fresno	0.782*	0.360*	5.500*	0.415*	0.00	3.000*	1.000*	0.600*	219,182*
	(0.019)	(0.019)	0.000	(0.002)		(0.998)	(0.284)	(0.084)	
Madera	0.727*	0.228*	5.955*	0.439*	0.00	0.423*	0.063*	0.026*	1,891*
	(0.050)	(0.022)	(0.000)	(0.003)		(0.050)	(0.022)	(0.003)	
Tulare	0.637*	0.259*	4.200*	0.432*	0.00	0.641*	0.252*	0.434*	4,592*
	(0.033)	(0.026)	0.000	(0.003)		(0.000)	(0.000)	(0.000)	

Notes: Bootstrapped standard errors in parentheses. A statistically significant result from the likelihood ratio test indicates that the model with unobserved heterogeneity produces a statistically significant improvement in the ability of the model to fit data. Significance code: * $p<0.05$.

Table 3: Results for CRRA Utility (Model 2: β=0.9996)

	With Unobserved Heterogeneity				
		Coefficient on:			
	PMI	i_t / ρ_{tz}	Susceptibility	Coefficient of Relative Risk Aversion	Susceptible Proportion
<u>Wine Grape Growers</u>					
Central Valley					
Fresno	-8.230*	0.099*	0.318*	0.698*	0.000
	(0.163)	(0.982)	(0.000)	(0.000)	
Madera	-0.666*	0.420*	0.335*	0.698*	0.021
	(0.000)	(0.000)	(0.000)	(0.000)	
San Joaquin	-1.122*	-0.115	2.887*	0.693*	0.000
	(0.009)	(0.100)	(0.000)	(0.000)	
North Coast					
Mendocino	-1.534*	2.883*	0.334*	0.600*	0.011
	(0.000)	(0.000)	(0.000)	(0.000)	
Napa	-3.749*	4.356	0.363	0.600	0.047
	(0.000)	(0.000)	(0.000)	(0.000)	
Sonoma	-1.204*	0.828*	4.521*	0.696*	0.001
	(0.004)	(0.000)	(0.000)	(0.000)	
Central Coast					
San Luis Obispo	-0.239*	1.147*	3.706*	0.702*	0.000
	(0.029)	(0.000)	(0.000)	(0.000)	
<u>Raisin Grape Growers</u>					
Central Valley					
Fresno	-0.229*	0.265*	1.000*	0.698*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	
Madera	-0.447*	0.433*	0.195*	0.711*	0.008
	(0.000)	(0.000)	(0.000)	(0.000)	
Tulare	-0.273*	-0.071	0.080*	0.668*	0.023
	(0.009)	(0.187)	(0.000)	(0.002)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Table 4: Likelihood Ratio Test: Model 2 ($\beta = 0.9996$) vs. Model 1 ($\beta = 0.9$)

	Test Statistic
<u>Wine Grape Growers</u>	
Central Valley	
Fresno	5,274*
Madera	-4,681
San Joaquin	-18,282
North Coast	
Mendocino	-2,778
Napa	6,654*
Sonoma	-30,002
Central Coast	
San Luis Obispo	-21,074
<u>Raisin Grape Growers</u>	
Central Valley	
Fresno	-4,208
Madera	-512
Tulare	-3,071

Note: A statistically significant result from the likelihood ratio test indicates that Model 2 ($\beta = 0.9996$) produces a statistically significant improvement in the ability of the model to fit data. Significance code: * $p<0.05$.

Table 5: Results for Growers Pre- and Post- PMI Receipt (Model 1: β=0.9)

	Receive PMI					Do Not Receive PMI				
	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion
	PMI	i_t/ρ_{tz}	Susceptibility			PMI	i_t/ρ_{tz}	Susceptibility		
Wine Grape Growers										
Central Valley										
Fresno	-2.042	1.266	6.501*	0.579*	0.334	0.753*	0.240*	2.833*	0.594*	0.247
	(1519.000)	(721.160)	(2.828)	(0.132)		(0.168)	(0.059)	(0.287)	(0.012)	
Madera	0.754*	0.438*	5.500*	0.506*	0.007	0.321*	0.283*	0.932*	0.693*	0.039
	(0.198)	(0.083)	(0.000)	(0.020)		(0.512)	(0.233)	(0.152)	(0.017)	
San Joaquin	5.731*	0.891*	0.899*	1.600*	0.000	5.757*	0.894*	1.000*	1.500*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
North Coast										
Mendocino	4.816*	0.929*	1.000*	1.100*	0.000	4.792*	0.931*	1.000*	1.100*	0.019
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Napa	-0.588	0.934*	9.516*	0.626*	0.987	0.817*	0.029*	14.734*	0.616*	0.999
	(0.576)	(0.168)	(0.991)	(0.006)		(0.360)	(0.162)	(1.383)	(0.005)	
Sonoma	1.751*	4.962*	9.999*	1.469*	0.007	-0.257	0.433*	23.416*	0.485*	0.976
	(0.000)	(0.000)	(0.000)	(0.000)		(0.144)	(0.095)	(0.554)	(0.022)	
Central Coast										
San Luis Obispo	5.846*	0.943*	0.980*	1.400*	0.002	6.878*	0.949*	1.000*	1.100*	0.006
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Raisin Grape Growers										
Central Valley										
Fresno	0.729*	0.444*	5.800*	0.412*	0.000	0.716*	0.692*	5.499*	0.525*	0.000
	(0.024)	(0.027)	(0.000)	(0.003)		(0.096)	(0.073)	(0.156)	(0.009)	
Madera	0.585*	0.261*	6.000*	0.442*	0.000	0.725*	0.242*	6.000*	0.439*	0.000
	(0.088)	(0.034)	(0.000)	(0.005)		(0.044)	(0.024)	(0.000)	(0.003)	
Tulare	0.070*	0.112*	2.231*	0.146*	0.897	0.606*	0.264*	4.994*	0.434*	0.000
	(0.069)	(0.049)	(0.645)	(0.605)		(0.038)	(0.019)	(0.000)	(0.003)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Table 6: Difference in Average Annual Welfare With and Without the PMI (Model 1: β=0.9)

	Average Annual Welfare		
	With PMI	Without PMI	Difference
<u>Wine Grape Growers</u>			
Central Valley			
Fresno	100.00	99.71	0.29
	(0.04)	(0.07)	
Madera	83.86	84.53	-0.67
	(0.11)	(0.04)	
San Joaquin	57.77	57.77	0.00
	(0.25)	(0.25)	
North Coast			
Mendocino	67.29	67.29	0.01
	(0.47)	(0.47)	
Napa	83.68	83.68	0.00
	(0.00)	(0.00)	
Sonoma	0.25	101.48	-101.23
	(0.00)	(0.00)	
Central Coast			
San Luis Obispo	83.34	83.34	0.00
	(0.31)	(0.31)	
<u>Raisin Grape Growers</u>			
Central Valley			
Fresno	76.24	73.64	2.06
	(0.13)	(0.16)	
Madera	60.35	60.17	0.18
	(0.20)	(0.22)	
Tulare	96.88	78.97	17.91
	(0.22)	(0.52)	

Notes: Standard deviations in parentheses. Values standardized so that the value of welfare for growers in Fresno county with PMI use is equal to 100. The difference in average annual grower welfare with and without the PMI is a measure of the value to the growers of the PMI disease forecast information.

Table 7: Difference in Average Annual Welfare With and Without the PMI (Model 2: β=0.9996)

	Average Annual Welfare		
	With PMI	Without PMI	Difference
Wine Grape Growers			
Central Valley			
Fresno	100.00	92.78	7.22
	(0.05)	(0.21)	
Madera	63.40	78.70	-15.29
	(0.29)	(0.21)	
San Joaquin	71.22	71.93	-0.71
	(0.14)	(0.11)	
North Coast			
Mendocino	78.70	79.92	-1.22
	(0.40)	(0.28)	
Napa	72.98	77.43	-4.45
	(0.15)	(0.11)	
Central Coast			
San Luis Obispo	99.08	101.89	0.00
	(0.23)	(0.19)	
Raisin Grape Growers			
Central Valley			
Fresno	73.48	75.22	-1.74
	(0.09)	(0.07)	
Madera	60.13	59.34	0.79
	(0.18)	(0.23)	
Tulare	94.72	93.99	0.73
	(0.23)	(0.27)	

Notes: Standard deviations in parentheses. Values standardized so that the value of welfare for growers in Fresno county with PMI use is equal to 100. The difference in average annual grower welfare with and without the PMI is a measure of the value to the growers of the PMI disease forecast information.

Appendix

Appendix A. Supplementary Tables and Figures

Table A.1: Data Dimensions

	Number of Growers			Number of Plots			Grower-Plot years		Grower-Plot Days		Number of Sprays	
	PMI users	PMI non-users	Total	PMI users	PMI non-users	Total	no PMI use	with PMI use	no PMI use	with PMI use	no PMI use	with PMI use
Wine Grape Growers												
Central Valley												
Fresno	1	4	5	4	51	55	398	8	97,510	1,960	5,395	39
Madera	2	3	5	44	35	79	152	171	37,240	41,895	1,242	1,546
San Joaquin	6	3	9	73	22	95	233	572	57,085	140,140	1,113	4,750
North Coast												
Napa	5	3	8	218	3	221	116	792	28,420	194,040	1,404	5,643
Sonoma	16	3	19	110	70	180	679	424	166,355	103,880	7,979	6,124
Mendocino	1	3	4	40	3	43	69	219	16,905	53,655	616	1,521
Central Coast												
San Luis Obispo	10	7	17	44	22	66	191	284	46,795	69,580	3,249	5,022
Raisin Grape Growers												
Central Valley												
Fresno	29	9	38	202	51	253	809	1,208	393,357	24,776	6,225	10,361
Madera	4	1	5	20	10	30	150	143	31,951	28,598	1,006	773
Tulare	6	2	8	12	37	49	293	67	57,705	11,934	1,917	406

Sources: Survey data; PUR records.

Table A.2: Spray Intervals Based on Disease Pressure Using the Powdery Mildew Index

Index	Disease pressure	Pathogen status	Suggested spray schedule							
				$a_t = 1$		$a_t = 2$			$a_t = 3$	
				Sulfur	**Contact**	**Sterol inhibitors**	**Strobilurins**	**Cell-signaling inhibitors**	**Biologicals SARs**	**Other**
0–30	Low	present	Spray interval	14–21 days	10–18 days	21 days	21 days	14–21 days	7–14 days	unknown
			ρ_z	21	21*	21	21	21	14	14
30–59	Intermediate	reproduces every 15 days	Spray interval	10–17 days	10–14 days	21 days	21 days	14–21 days	7 days	unknown
			ρ_z	14*	14	21	21	21	7	7
60 and above	High	reproduces every 5 days	Spray interval	7 days	7 days	10-14 days	14 days	14 days	use not recommended	unknown
			ρ_z	7	7	14	14	14	0	0

Note: Value of ρ_z rounded to the nearest category value to keep the number of ρ_z categories equal to four (ρ_z=0,7,14,21)

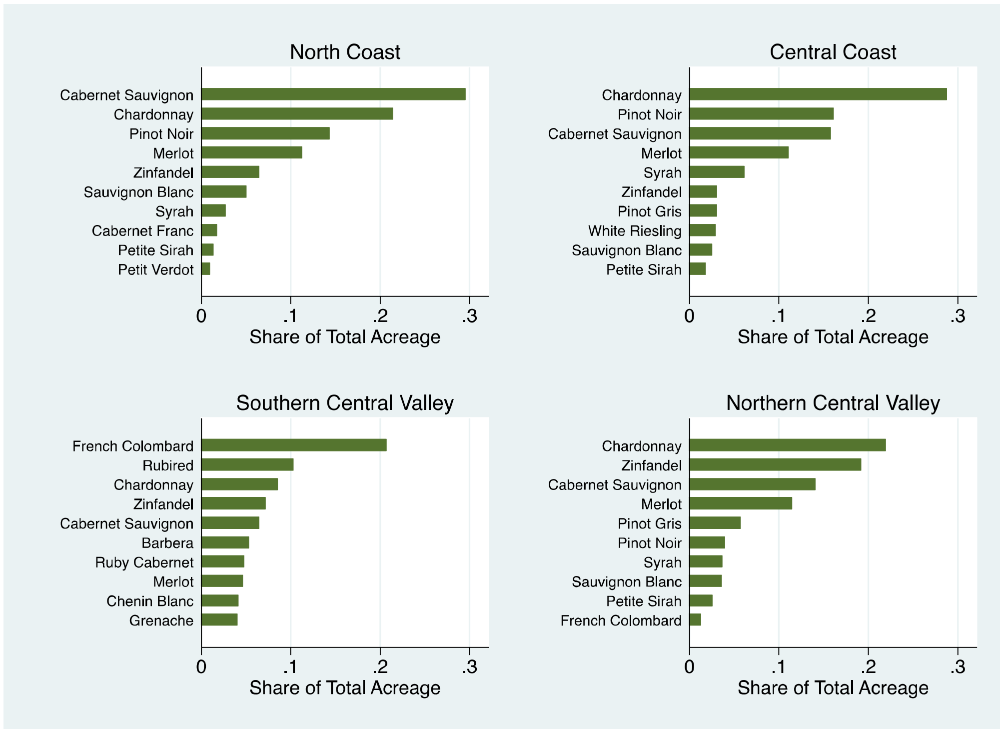
Source: UC IPM, UC Management Guidelines for Powdery Mildew on Grape, available at http://www.ipm.ucdavis.edu/PMG/r302100311.html

Table A.3: Evolution of Current Protection (ρ_Z) Based on Chemical Last Sprayed and the PMI

	Last Spray=1	Last Spray=2	Last Spray=3
PMI=1	21	21	14
PMI=2	14	21	7
PMI=3	7	14	0

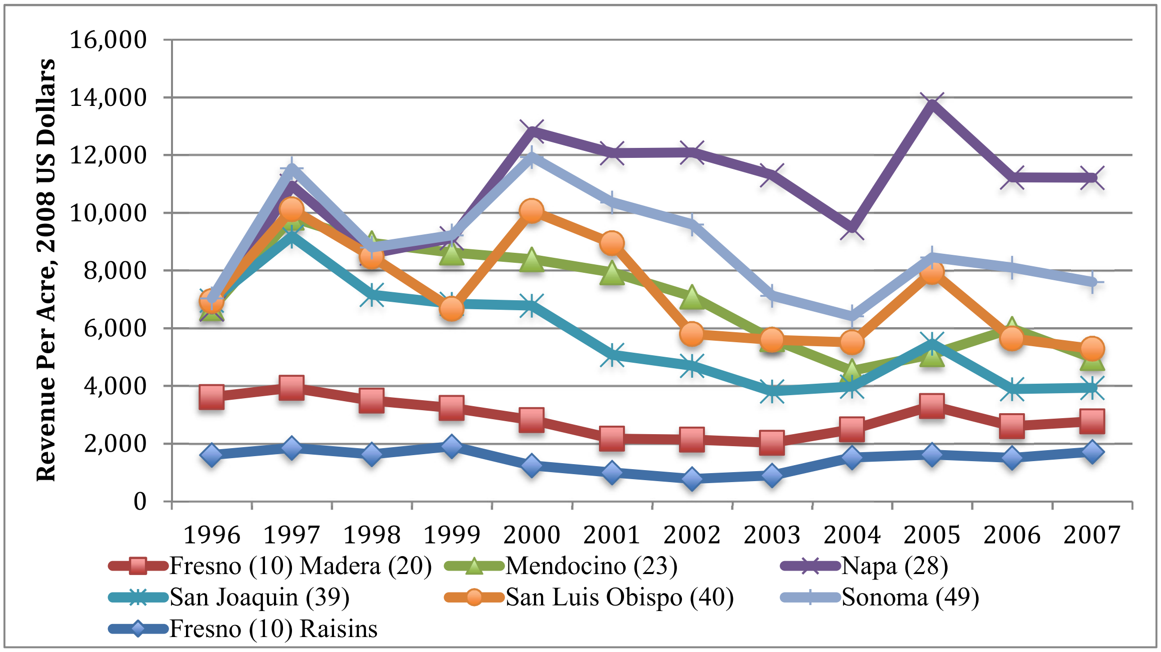
Source: Summarized from Table A.2.

Figure A.1: Top Ten Varieties by Share of Bearing Acreage, 2011



Source: USDA/NASS Acreage Reports, 2011.

Figure A.2: Average Revenue Per Acre



Note: Raisins are reported as fresh equivalent of dried fruit. Prices are in 2008 US dollars, converted using the BEA GDP deflator.
Source: USDA (2003–2012).

Table A.4: Average Spraying Costs Per Acre for Major Chemical Categories

Chemical Category	Application Costs ($)	Material Costs ($)	Total ($)
Sterol Inhibitors	26	31	57
Strobilurins	26	31	57
Cell-Signaling Inhibitors	17	31	48
Sulfur	11	2	13
Biologicals	22	31	53
Contact	17	31	48
Other	22	31	53
SARs	22	31	53

Note: Costs are in 2011 US dollars.
Sources: Derived from UCCE (2003-2013).

Table A.5: Average Per Acre Spraying Costs by Region, 2011

	North Coast	Central Coast	North and South Valley
	Cost per acre	Cost per acre	Cost per acre
Chemical Category	*$ per acre*	*$ per acre*	*$ per acre*
Sulfur or Contact	18	13	13
Synthetics	76	61	57
Other	55	51	52

Note: Costs are in 2011 US dollars.
Sources: Derived from UCCE (2003-2013).

Table A.6: Robustness Check: Results for Close Stations Only (Model 1: β=0.9)

	With Unobserved Heterogeneity				
	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion
	PMI	i_t/ρ_{tz}	Susceptibility		
Wine Grape Growers					
Central Valley					
Fresno	0.811*	0.111	3.111*	0.574*	0.332
	(0.211)	(0.074)	(0.386)	(0.032)	
Madera		*insufficient data*			
i					
San Joaquin	4.215*	0.887*	1.000*	1.100*	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	
North Coast					
Mendocino	4.796*	0.926*	1.000*	1.100*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	
Napa	-0.878	1.012*	10.400*	0.624*	0.969
	(0.600)	(0.157)	(1.123)	(0.007)	
Sonoma	4.722*	1.535*	39.980*	0.678*	0.000
	(0.498)	(0.360)	(0.000)	(0.011)	
North Coast					
San Luis Obispo	5.851*	0.923*	1.000*	1.100*	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	
Raisin Grape Growers					
Central Valley					
Fresno	0.762*	0.419*	6.000*	0.412*	0.000
	(0.026)	(0.023)	(0.000)	(0.002)	
Madera	0.753*	0.238*	6.000*	0.438*	0.000
	(0.039)	(0.020)	(0.000)	(0.003)	
Tulare	0.632*	0.291*	4.500*	0.429*	0.000
	(0.038)	(0.038)	(0.000)	(0.004)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Table A.7: Results for Growers Pre- and Post- PMI Receipt (Model 2: β=0.9996)

	Receive PMI					Do Not Receive PMI				
	Coefficient on:			Coefficient of		Coefficient on:			Coefficient of	
	PMI	$^{i_t}/_{\rho_{tz}}$	Susceptibility	Relative Risk Aversion	Susceptible Proportion	PMI	$^{i_t}/_{\rho_{tz}}$	Susceptibility	Relative Risk Aversion	Susceptible Proportion
<u>Wine Grape Growers</u>										
Central Valley										
Fresno	-0.999*	1.161	0.050	0.693	0.040	-5.974*	-0.250*	0.525*	0.576*	0.004
	(0.050)	(12.526)	(7.220)	(15.479)		(0.000)	(0.000)	(0.000)	(0.000)	
Madera	-0.831*	1.078*	1.807*	0.705*	0.000	-1.196*	0.095*	0.523*	0.669*	0.017
	(0.029)	(0.000)	(0.001)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
San Joaquin	-0.743*	-0.194	0.236*	0.666*	0.015	-1.060*	-0.118*	2.900*	0.691*	0.000
	(0.031)	(0.600)	(0.001)	(0.068)		(0.001)	(0.002)	(0.000)	(0.000)	
North Coast										
Mendocino	-1.522*	2.901*	0.312*	0.696*	0.018	-1.720*	2.521*	0.145*	0.715*	0.167
	(0.000)	(0.000)	(0.000)	(0.000)		(0.728)	(1.066)	(0.061)	(1.321)	
Napa	-16.085*	-0.850	-1.067	0.488*	0.999	-1.292*	-0.059*	0.121*	0.671*	0.918
	(1.426)	(3.841)	(0.666)	(0.037)		(0.000)	(0.000)	(0.000)	(0.000)	
Central Coast										
San Luis Obispo	0.096*	1.640*	3.706*	0.699*	0.001	-0.409*	0.579*	3.705*	0.698*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
<u>Raisin Grape Growers</u>										
Central Valley										
Fresno	-0.110*	0.388*	1.000*	0.696*	0.000	-0.270*	0.197*	1.000*	0.694*	0.001
	(0.001)	(0.000)	(0.000)	(0.000)		(0.001)	(0.001)	(0.000)	(0.000)	
Madera	-0.231*	0.049*	1.000*	0.714*	0.000	-0.496*	0.211*	0.046*	0.713*	0.157
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Tulare	-0.348*	-0.040*	1.000*	0.701*	0.002	-0.353*	0.049*	1.000*	0.697*	0.000
	(0.000)	(0.002)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Table A.8: Results for Years of Low, Medium, and High Powdery Mildew Pressure

	Low PM Pressure					Medium PM Pressure					High PM Pressure				
	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion
	PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.		
Wine Grape Growers															
Central Valley															
Fresno	0.931*	0.124*	3.660*	0.535*	0.463	*insufficient data*					1.646*	0.190*	4.900*	0.594*	0.000
	(0.134)	(0.074)	(0.305)	(0.018)							(0.126)	(0.078)	(0.000)	(0.009)	
Madera	-1.654	1.084*	4.085*	0.650*	0.563	-2.291	2.141*	2.592*	0.682*	0.010	0.316	0.303	4.355*	0.696*	0.125
	(0.982)	(0.127)	(0.000)	(0.016)		(1.131)	(0.353)	(0.490)	(0.026)		(0.483)	(0.239)	(0.692)	(0.010)	
San Joaquin	4.226*	0.877*	1.000*	1.100*	0.007	4.208*	0.865*	1.000*	1.100*	0.036	4.213*	0.888*	1.000*	1.100*	0.002
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
North Coast															
Mendocino	4.811*	0.920*	1.000*	1.100*	0.012	4.812*	0.927*	1.000*	1.100*	0.045	4.816*	0.921*	1.000*	1.100*	0.016
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Napa	-6.727*	2.573*	15.624*	0.632*	0.947	-1.135	0.849*	15.162*	0.633*	0.958	2.047*	0.452*	5.535*	0.630*	0.970
	(0.950)	(0.405)	(1.326)	(0.004)		(0.937)	(0.566)	(1.550)	(0.020)		(0.452)	(0.214)	(1.062)	(0.004)	
Sonoma	26.463*	-0.112	0.033*	0.389*	0.158	-0.311	0.418*	23.571*	0.488*	1.000	7.587*	9.268*	0.993*	1.413*	0.027
	(0.171)	(0.170)	(0.017)	(0.492)		(0.171)	(0.138)	(0.837)	(0.035)		(0.000)	(0.000)	(0.000)	(0.000)	
Central Coast															
San Luis Obispo	5.844*	0.942*	1.000*	1.100*	0.023	5.854*	0.943*	1.000*	1.100*	0.004	5.865*	0.938*	1.000*	1.100*	0.013
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Raisin Grape Growers															
Central Valley															
Fresno	3.711*	-0.098	5.200*	0.480*	0.000	3.211*	2.033*	4.000*	0.455*	0.000	3.183*	3.200*	4.000*	0.550*	0.012
	(0.626)	(0.062)	(0.000)	(0.095)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Madera	0.678*	0.245*	5.998*	0.439*	0.000	0.652*	0.212*	6.000*	0.442*	0.000	0.714*	0.265*	6.000*	0.445*	0.000
	(0.077)	(0.031)	(0.000)	(0.003)		(0.087)	(0.030)	(0.000)	(0.005)		(0.055)	(0.031)	0.000	(0.003)	
Tulare	0.211*	0.175*	1.887*	0.336*	0.522	0.510*	0.372*	10.787*	0.427*	0.000	0.669*	0.201*	5.869*	0.443*	0.000
	(0.096)	(0.025)	(0.212)	(0.054)		(0.050)	(0.029)	(0.862)	(0.006)		(0.033)	(0.022)	0.000	(0.003)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Table A.9: Results for Years of Low, Medium, and High Powdery Mildew Pressure: Growers Who Receive the PMI

	Low PM Pressure					Medium PM Pressure					High PM Pressure				
	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion
	PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.		
Wine Grape Growers															
Central Valley															
Fresno	-5.792	3.133*	9.224*	0.630*	0.355	*insufficient data*					-0.060	0.590*	5.000*	0.527*	0.000
	(3.192)	(0.177)	(0.142)	(0.017)							(0.051)	(0.088)	(0.000)	(0.008)	
Madera	-1.232*	1.494*	1.000*	0.717*	0.000	-3.919*	3.400*	1.000*	0.746*	0.000	-0.452	0.744*	1.000*	0.681*	0.000
	(0.228)	(0.147)	(0.000)	(0.015)		(0.729)	(0.441)	(0.000)	(0.027)		(0.196)	(0.069)	(0.000)	(0.008)	
San Joaquin	4.225*	0.883*	1.000*	1.100*	0.000	4.213*	0.859*	1.000*	1.100*	0.010	4.206*	0.892*	1.000*	1.100*	0.003
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
North Coast															
Mendocino	4.813*	0.915*	1.000*	1.100*	0.015	4.810*	0.929*	1.000*	1.100*	0.048	4.825*	0.922*	1.000*	1.100*	0.020
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Napa	11.731*	1.868*	0.998*	1.600*	0.017	*insufficient data*					1.199*	0.616*	6.332*	0.630*	0.985
	(0.186)	(0.321)	(0.082)	(0.598)							(0.537)	(0.213)	(0.810)	(0.005)	
Sonoma	26.098*	0.152	0.012	0.389	0.152	7.994*	9.367*	0.996*	1.029*	4964	7.806*	9.357*	0.998*	1.249*	0.040
	(0.217)	(0.262)	(0.016)	(0.500)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Central Coast															
San Luis Obispo	5.828*	0.948*	1.000*	1.100*	0.035	5.863*	0.932*	1.000*	1.100*	0.000	5.859*	0.962*	1.000*	1.100*	0.010
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Raisin Grape Growers															
Central Valley															
Fresno	3.749*	-0.045	5.200*	0.468*	0.000	0.703*	0.497*	7.000*	0.408*	0.000	2.131*	1.757*	4.000*	0.642*	0.000
	(0.548)	(0.089)	(0.000)	(0.088)		(0.024)	(0.037)	(0.000)	(0.003)		(0.000)	(0.000)	(0.000)	(0.000)	
Madera	0.639*	0.247*	6.000*	0.439*	0.000	0.531*	0.249*	6.000*	0.446*	0.000	0.492*	0.780*	6.000*	0.445*	0.000
	(0.099)	(0.042)	(0.000)	(0.005)		(0.077)	(0.029)	(0.000)	(0.004)		(0.000)	(0.000)	(0.000)	(0.000)	
Tulare	0.720*	0.393*	4.500*	0.413	0.000	3.259*	-0.116*	4.500*	0.807*	0.000	3.544*	4.649*	4.500*	1.100*	0.415
	(0.209)	(0.167)	(0.000)	(0.016)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Table A.10: Results for Years of Low, Medium, and High Powdery Mildew Pressure: Growers Who Do Not Receive the PMI

	Low PM Pressure					Medium PM Pressure					High PM Pressure				
	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion
	PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.		
Wine Grape Growers															
Central Valley															
Fresno	1.886*	0.078*	5.000*	0.604*	0.000	*insufficient data*					1.655*	0.189*	5.000*	0.595*	0.000
	(0.122)	(0.059)	(0.000)	(0.007)							(0.010)	(0.088)	(0.000)	(0.008)	
Madera	-1.002*	0.886*	1.001*	0.621*	0.002	-1.100	1.394*	1.295*	0.604*	0.006	0.482	0.166	0.696*	0.739*	0.035
	(0.456)	(0.166)	(0.239)	(0.025)		(0.695)	(0.383)	(0.368)	(0.037)		(0.573)	(0.262)	(0.177)	(0.020)	
San Joaquin	4.237*	0.831*	1.000*	1.100*	0.059	4.191*	0.890*	1.000*	1.100*	0.089	4.217*	0.884*	1.000*	1.100*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
North Coast															
Mendocino	4.796*	0.926*	1.000*	1.100*	0.000	4.816*	0.924*	1.000*	1.100*	0.000	4.800*	0.918*	1.000*	1.100*	0.029
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Napa	5.836*	0.665*	0.315*	0.628*	0.248	-1.135	0.849*	15.162*	0.633*	0.958	4.801*	0.107	3.577*	0.617*	0.631
	(0.000)	(0.000)	(0.000)	(0.000)		(0.937)	(0.566)	(1.550)	(0.020)		(0.564)	(0.244)	(0.947)	(0.010)	
Sonoma	27.185*	-0.644	0.201*	0.389	0.175	-0.241	0.054	26.451*	0.389*	0.998	0.720*	0.393*	4.500*	0.413*	0.027
	(0.283)	(0.341)	(0.041)	(0.498)		(0.360)	(0.171)	(0.592)	(0.025)		(0.209)	(0.167)	(0.000)	(0.016)	
Central Coast															
San Luis Obispo	5.857*	0.938*	1.000*	1.100*	0.000	5.852*	0.945*	1.000*	1.100*	0.008	5.859*	0.947*	1.000*	1.100*	0.013
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Raisin Grape Growers															
Central Valley															
Fresno	0.728*	0.329*	4.999*	0.414*	0.000	0.747*	0.259*	5.988*	0.414*	0.000	0.728*	0.329*	4.999*	0.414*	0.000
	(0.030)	(0.002)	(0.000)	(0.003)		(0.084)	(0.044)	(0.000)	(0.000)		(0.095)	(0.002)	(0.000)	(0.001)	
Madera	0.727*	0.243*	5.974*	0.438*	0.000	0.889*	0.176*	-2.143	0.434*	0.286	0.713*	0.259*	6.000*	0.446*	0.000
	(0.060)	(0.037)	(0.000)	(0.004)		(0.075)	(0.034)	(1.748)	(0.008)		(0.058)	(0.029)	(0.000)	(0.004)	
Tulare	0.340*	0.146*	1.491*	0.276*	0.451	3.235*	-0.290	4.500*	0.526*	0.000	0.673*	0.204*	4.496*	0.442*	0.000
	(0.094)	(0.020)	(0.199)	(0.057)		(0.000)	(0.180)	(0.000)	(0.000)		(0.034)	(0.019)	(0.000)	(0.002)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * p<0.05.

Table A.11: Results for Years of Low, Medium, and High Revenue Per Acre

	Low Per Acre Revenue					**Medium Per Acre Revenue**					**High Per Acre Revenue**				
	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Suscept. Proportion
	PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept			PMI	i_t/ρ_{tz}	Suscept.		
Wine Grape Growers															
Central Valley															
Fresno			*insufficient data*			0.499*	0.238*	4.237*	0.484*	0.820	-0.047	0.165*	4.866*	0.401*	0.910
						(0.156)	(0.049)	(0.456)	(0.039)		(0.078)	(0.023)	(0.263)	(0.011)	
Madera			*insufficient data*			-0.030	0.413*	1.946*	0.522*	0.817	2.751*	0.094*	0.996*	2.088*	0.024
						(0.325)	(0.098)	(0.414)	(0.026)		(0.000)	(0.000)	(0.000)	(0.000)	
San Joaquin			*insufficient data*					*insufficient data*			4.268*	0.903*	1.000*	1.100*	0.006
											(0.000)	(0.000)	(0.000)	(0.000)	
North Coast															
Mendocino			*insufficient data*			4.807*	0.922*	1.000*	1.100*	0.221	-0.690	0.065	0.998*	0.464*	2E-06
						(0.000)	(0.000)	(0.000)	(0.000)		(0.736)	(0.297)	(0.010)	(0.032)	
Napa	-0.263	0.072*	30.001*	0.802*	0.951	0.648	0.615*	6.355*	0.639*	0.940			*insufficient data*		
	(0.238)	(0.302)	(0.295)	(0.015)		(0.735)	(0.252)	(0.872)	(0.005)						
Sonoma	6.944*	1.383*	19.834*	0.628*	0.975	3.551*	3.232*	-9.460	0.670*	0.173	29.997*	9.998*	20.000*	1.600*	0.171
	(0.130)	(0.193)	(0.613)	(0.238)		(0.642)	(0.519)	(5.447)	(0.012)		(0.000)	(0.000)	(0.000)	(0.000)	
Central Coast															
San Luis Obispo			*insufficient data*			5.792*	0.952*	1.000*	1.100*	0.286	5.875*	0.967*	1.000*	1.100*	0.032
						(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Raisin Grape Growers															
Central Valley															
Fresno	1.311	1.072*	0.896*	0.743*	0.000	2.189*	4.319*	3.653*	0.469*	0.056	1.824*	0.562*	6.595*	0.494*	3E-09
	(0.048)	(0.035)	(0.000)	(0.049)		(0.000)	(0.000)	(0.000)	(0.002)		(0.047)	(0.050)	(0.000)	(0.002)	
Madera	1.962*	1.765*	0.974*	0.671*	0.164	0.851*	0.244*	6.000*	0.451*	0.000	1.742*	0.385*	8.000*	0.512*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.042)	(0.020)	(0.000)	(0.002)		(0.089)	(0.055)	(0.000)	(0.005)	
Tulare	-0.251	0.199*	1.421*	0.587*	0.533	0.779*	0.248*	4.499*	0.447*	0.000	6.946*	-0.433	5.000*	0.277	0.000
	(0.132)	(0.042)	(0.232)	(0.032)		(0.040)	(0.025)	(0.000)	(0.003)		(1.469)	(0.213)	(0.000)	(0.384)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * p<0.05.

Table A.12: Results for Years of Low, Medium, and High Revenue Per Acre: Growers Who Receive the PMI

	Low Per Acre Revenue					Medium Per Acre Revenue					High Per Acre Revenue				
	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion
	PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.		
Wine Grape Growers															
Central Valley			*insufficient data*			-0.189	0.343*	3.823*	0.413*	0.652	0.337	0.054	1.960*	0.493*	0.054
						(0.295)	(0.100)	(0.345)	(0.018)		(0.536)	(0.296)	(0.844)	(0.026)	
North Coast	-0.733	0.427*	25.530*	0.686*	0.614	-0.186	0.064*	23.684*	0.475*	0.997	4.400*	-0.001	1.994*	0.708*	0.497
	(0.952)	(0.100)	(2.900)	(0.023)		(0.166)	(0.131)	(0.928)	(0.021)		(0.738)	(0.533)	(0.615)	(0.017)	
Central Coast			*insufficient data*			5.834*	0.946*	1.000*	1.100*	0.086	5.878*	0.970*	1.000*	1.100*	0.014
						(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
Raisin Grape Growers															
Central Valley	1.304*	1.367*	1.000*	0.664*	0.000	0.970*	0.535*	-1.722	0.430*	0.380	3.241*	2.627	4.965*	0.656*	0.019
	(0.000)	(0.000)	(0.000)	(0.000)		(0.024)	(0.030)	(0.965)	(0.004)		(0.000)	(0.000)	(0.000)	(0.000)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Table A.13: Results for Years of Low, Medium, and High Revenue Per Acre: Growers Who Do Not Receive the PMI

	Low Per Acre Revenue					**Medium Per Acre Revenue**					**High Per Acre Revenue**				
	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion	Coefficient on:			Coefficient of Relative Risk Aversion	Susceptible Proportion
	PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.			PMI	i_t/ρ_{tz}	Suscept.		
Wine Grape Growers															
Central Valley	0.286	0.881*	-34.897	0.610*	0.044	0.654*	0.243*	3.565*	0.410*	0.495	-1.074*	0.423*	3.476*	0.483*	0.49
	(0.263)	(0.141)	(26.863)	(0.011)		(0.078)	(0.028)	(0.184)	(0.012)		(0.172)	(0.070)	(0.301)	(0.008)	
North Coast	-0.217*	0.409*	24.143*	0.687*	0.986	-0.023	0.462*	20.935*	0.536*	0.980	-0.848*	1.240*	15.164*	0.577*	0.990
	(0.085)	(0.120)	(0.392)	(0.192)		(0.222)	(0.158)	(1.017)	(0.021)		(0.360)	(0.463)	(2.299)	(0.018)	
Central Coast			*insufficient data*												
Raisin Grape Growers															
Central Valley	2.504*	-0.250*	0.892*	0.654*	0.043	0.813*	0.319*	5.996*	0.438*	0.000	1.780*	0.489*	17.662*	0.499*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.023)	(0.023)	(0.853)	(0.002)		(0.048)	(0.043)	(0.509)	(0.002)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Appendix B. Likelihood Ratio Tests

We conduct four types of likelihood ratio tests.[9] The first likelihood ratio test tests between the model with unobserved heterogeneity and the model without unobserved heterogeneity, for each type of utility function. The model without unobserved heterogeneity is a special case of (and therefore a constrained version with fewer parameters than) the model with unobserved heterogeneity.

The test statistic D is given by:

$$D = 2L^a - 2L^o, \tag{B.1}$$

where L^a is the log likelihood of the model with unobserved heterogeneity and L^o is the log likelihood of the model without unobserved heterogeneity. The test statistic D is distributed chi-squared with 1 degree of freedom (since the number of parameters in the model with unobserved heterogeneity minus the number of parameters in the model without unobserved heterogeneity = 1 degree of freedom). If the test statistic D is greater than the critical value 0.0039, then the coefficient on unobserved heterogeneity is statistically significant at a 5% level and the model with unobserved heterogeneity produces a statistically significant improvement in the ability of the model to fit data.

Table B.1 presents the results of the likelihood ratio tests between the model with unobserved heterogeneity and the model without unobserved heterogeneity for each of the following utility functions: the linear utility, log utility, and linear utility with PMI squared.[10] In almost all cases, the model with unobserved heterogeneity produces a statistically significant improvement in the ability of the model to fit data.

In the second likelihood ratio test, we test between log utility and CRRA utility since log utility is a special case of CRRA utility where $\gamma = 1$. The test statistic D is given by Equation (B.1), where L^a is now the log likelihood of the CRRA utility model and L^o is now the log likelihood of the log utility model. The test statistic D is distributed chi-squared with 1 degree of freedom (since 4 parameters in the CRRA utility model minus 3 parameters in the log utility model = 1 degree of freedom). If the test statistic D is greater than the critical value 0.0039, then the

[9] The first three likelihood ratio tests use Model 1, as results of the fourth likelihood ratio test show that Model 2 does not provide significant improvement over Model 1 in the ability of the model to fit the data.

[10] Results of the likelihood ratio tests between the model with unobserved heterogeneity and the model without unobserved heterogeneity for CRRA utility are presented in Table 4 of the paper.

CRRA model produces a statistically significant improvement in the ability of the model to fit data at a 5% level.

Table B.2 presents the results of likelihood ratio tests between CRRA utility with unobserved heterogeneity and log utility with unobserved heterogeneity. CRRA utility produces improvement in the ability of the model to fit data in all cases except for raisin growers in Fresno and Madera. In addition, many of the coefficients using the logarithmic model are negative and significant, as seen in the estimates from the logarithmic utility with unobserved heterogeneity in Table B.3. The two models for which CRRA utility does not produce a statistically significant improvement over logarithmic utility in the ability of the model to fit the data do not have any significantly negative coefficients in the log utility model. For all models for which we have significant negative coefficients in the log model, the CRRA utility produces a statistically significant improvement over log utility in the ability of the model to fit the data.

In the third likelihood ratio test, we test between utility with PMI squared and linear utility to see if farmers are risk averse. The linear model is a special case of the PMI squared model. The test statistic D is given by Equation (B.1), where L^a is now the log likelihood of the PMI squared utility model and L^o is now the log likelihood of the linear utility model. The test statistic D is distributed chi-squared with 1 degree of freedom (since 4 parameters in the PMI squared model minus 3 parameters in the linear model = 1 degree of freedom). If the test statistic D is greater than the critical value 0.0039, then the coefficient on PMI squared is statistically significant at a 5% level and the PMI squared model produces a statistically significant improvement in the ability of the model to fit data.

Table B.4 presents the results of likelihood ratio tests of linear utility versus utility with PMI squared, both with unobserved heterogeneity. Utility with PMI squared produces a statistically significant improvement in the ability of the model to fit data in most cases, but there are fewer differences in this case.

Based on these results, the model with unobserved heterogeneity generally better fits the data, and CRRA utility and utility with PMI squared are better fits to the data than log utility and linear utility, although linear utility is close to utility with PMI squared.

The fourth type of likelihood ratio test we conduct is between Model 1 ($\beta = 0.9$) and Model 2 ($\beta = 0.9996$). This test and its results are presented in Table 4 of the paper. According to the results, Model 2 generally does not provide significant improvement over Model 1 in the ability of the model to fit the data.

Table B.1: Likelihood Ratio Tests of Utility Functions With vs. Without Unobserved Heterogeneity

	Test statistic		
	Linear Utility	Log Utility	Utility with PMI Squared
Wine Grape Growers			
Central Valley			
Fresno	68,427*	29,169*	60,679*
Madera	0		
San Joaquin	18,398*	4,350*	13,176*
North Coast			
Mendocino	23,796*	4,038*	21,608*
Napa	59,652*	10,234*	37,828*
Sonoma	238,844*	71,440*	168,888*
Central Coast			
San Luis Obispo	42,998*	8,956*	28,146*
Raisin Grape Growers			
Central Valley			
Fresno	163,754*	247,590*	146,010*
Madera	16,655*	19,238*	14,825*
Tulare	50,396*	41,336*	47,378*

Notes: A statistically significant result from the likelihood ratio test indicates that the model with unobserved heterogeneity produces a statistically significant improvement in the ability of the model to fit data. Significance code: * p<0.05.

Table B.2: Likelihood Ratio Test: CRRA Utility With Unobserved Heterogeneity vs. Log Utility with Unobserved Heterogeneity

	Test Statistic
Wine Grape Growers	
Central Valley	
Fresno	1,822*
Madera	2,340*
San Joaquin	22,074*
North Coast	
Mendocino	8,233*
Napa	19,218*
Sonoma	9,678*
Central Coast	
San Luis Obispo	13,270*
Raisin Grape Growers	
Central Valley	
Fresno	-26,206
Madera	-2,511
Tulare	15,737*

Notes: A statistically significant result from the likelihood ratio test indicates that the CRRA model produces a statistically significant improvement in the ability of the model to fit data. Significance code: * $p<0.05$.

Table B.3: Logarithmic Utility With Unobserved Heterogeneity

	Coefficient on:			
	PMI	i_t/ρ_{tz}	Susceptibility	Susceptible Proportion
<u>Wine Grape Growers</u>				
Central Valley				
Fresno	-4.651*	0.659	6.333*	0.144
	(1.053)	(0.447)	(1.119)	
Madera	-9.468*	3.279*	-67.206	0.020
	(1.375)	(0.736)	(225.450)	
San Joaquin	-122.050*	33.926*	57.693*	0.038
	(6.580)	(1.975)	(7.991)	
North Coast				
Mendocino	-220.950*	61.158	-973.610	0.089
	(84.013)	(42.572)	(748.980)	
Napa	-77.860*	15.230*	125.650*	
	(7.700)	(4.184)	(0.000)	
Sonoma	-9.283*	2.168*	-55.017*	0.120
	(2.008)	(1.163)	(19.683)	
Central Coast				
San Luis Obispo	6.813*	5.346*	-153.170*	0.954
	(0.947)	(2.354)	(6.795)	
<u>Raisin Grape Growers</u>				
Central Valley				
Fresno	8.799*	7.128*	5.492*	0.010
	(0.000)	(0.000)	(0.000)	
Madera	2.169*	0.156*	5.200*	0.152
	(0.000)	(0.000)	(0.000)	
Tulare	2.173*	0.000*	4.515*	0.000
	(0.000)	(0.000)	(0.000)	

Notes: Bootstrapped standard errors in parentheses. Significance code: * $p<0.05$.

Table B.4: Likelihood Ratio Test: Linear Utility vs. Utility with PMI Squared, With Unobserved Heterogeneity

	Test Statistic
Wine Grape Growers	
Central Valley	
Fresno	-256
Madera	0
San Joaquin	80*
North Coast	
Mendocino	48*
Napa	4,550*
Sonoma	4*
Central Coast	
San Luis Obispo	10*
Raisin Grape Growers	
Central Valley	
Fresno	-4
Madera	2*
Tulare	-62

Notes: A statistically significant result from the likelihood ratio test indicates that the PMI squared model produces a statistically significant improvement in the ability of the model to fit data. Significance code: * $p<0.05$.