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Pesticide exposure and the physical and economic health of US crop workers

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Abstract

We examine the impact of pesticide exposure on crop worker health and earnings using 2002 through 2016 data from the US Department of Labor, Employment, and Training Administration's National Agricultural Workers Survey. Our findings show that pesticide exposure is positively related to certain health conditions and that wage patterns are consistent with compensating wage differentials. The offsetting impacts of these equilibrium aspects are limited by how wage premia for assumed health risks depend on worker bargaining power and agency. We document differences for undocumented versus documented workers with implications for compensation and occupational health policies in this labor-intensive, essential sector.

Keywords

compensating wage differentials; crop workers; health; pesticides; undocumented legal status

It is well known from research on a wide variety of industries that work-related risk is not equally distributed across occupations and settings (e.g., Lavetti, 2020 on Alaskan commercial fishing; Gertler et al., 2005 on sex work in Mexico). Crop workers are another group of interest from the perspective of occupational safety and health as these workers are often tasked with using heavy machinery and may be exposed to harmful chemicals, among other occupational hazards. In the United States, poor occupational safety and health records for this sector have led to the creation of the "National Occupational Research Agenda for Agriculture, Forestry and Fishing" under the Centers for Disease Control and Prevention (NORA Agriculture, Forestry, and Fishing Sector Council, 2008). The program is an active targeting effort to reduce workplace-related injuries and illnesses in this particular sector. From a labor economics perspective, the theory of compensating wage differentials is well established and formalizes the prediction that risk and other potential negative abstract aspects of a job such as unpleasantness will be compensated within equilibrium wages. This financial premium associated with the risky or unpleasant aspects of a job, however, should conceptually be a function of not only the job characteristics relative to other job possibilities but also reflective of general worker sorting based on preferences including heterogeneous attitudes toward risk. Worker agency as translated into bargaining

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power (or lack thereof) also may be significant to the determination of equilibrium worker outcomes. This decoupling of worker "choice" from the decision to partake in risk is particularly relevant to discussions of equitable pay and related public policy and to social costs (externalities) associated with negative health outcomes of financially poor workers. Pesticides are used to various degrees worldwide in recognition of substantial benefits in keeping agricultural goods free from insects and microorganisms (Fernandez-Cornejo et al., 1998), though pesticide poisonings of workers are also widespread (Reeves & Schafer, 2003). According to the US National Library of Medicine and the National Institute of Health, the United States uses 1 billion pounds of pesticides yearly. However, in a 2008 Agricultural Health Survey on pesticide users in Iowa and North Carolina, it was found that approximately 16% of the sample experienced at least one incidence of pesticide poisoning "or an unusually high pesticide exposure episode" in their lifetime (Alavanja, 2009). In the same study, it was observed that 12 out of 30 pesticides used worldwide were associated with an increased risk of some cancers, in particular those of the prostate, lung, colon, and/or pancreas. In addition to the increased risk of cancer, medical studies have documented fertility and pregnancy impacts in agricultural workers among other significant health conditions (some review articles include Bassil et al., 2007; Bhardwaj et al., 2018; Colborn & Carroll, 2007; Mehrpour et al., 2014; Sharma & Singhvi, 2017). In this article, we contribute to the literature by documenting compensating wage differentials related to pesticide-related health risk on US farms and the heterogeneity in receipt of these compensating differentials (which in turn has distributional implications for a wide range of public policies, including those on compensation and on health and safety practice). We ask what the earning implications are for US crop workers who are vulnerable to health-related ailments associated with pesticide exposure and how our findings can be used to inform policies that are cognizant of differences in the extent to which workers select their jobs in choice-based and choice-limited ways. Agriculture comprises a particularly compelling case study context to understand distributional elements of compensating wage differentials because of a relatively high percentage of undocumented workers. Legal status has been associated elsewhere with differences in compensation levels, which may be related to reductions in worker bargaining power at the point that compensation is determined (e.g., Isé & Perloff, 1995; Massey, 1987; Pena, 2010a, 2010b; Rivera-Batiz, 1999; Taylor, 1992). Our theoretical expectation then is that differences in bargaining power and agency will also be relevant to the determination of hazard-related compensation, all else being equal. Our empirical study tests this for all workers and for subsamples of piece rate (paid per unit of productivity [e.g., per crop picked]) and time rate (paid per unit of time [e.g., per hour]) workers to further understand how measurable productivity relates to our findings.

PREVIOUS LITERATURE AND CONCEPTUAL FRAMEWORK

In this section, we review agricultural and health literature on pesticide exposure in farm work and on compensating differentials and economic outcomes as a result of undesirable or unsafe working conditions. We also examine the literature on bargaining power and its relationship to compensating wages with particular attention to undocumented legal status.

Health literature on crop workers and pesticide exposure Our article contributes to the broader literature pertaining to the health and safety of farmworkers by examining determinants and impacts of exposure to health-related risks in US farm work restricted to channels pertaining to pesticides at a national representative level. In contrast, much of the existing literature is within public health and medical fields (e.g., Frank et al., 2004; Hansen & Donohoe, 2003; Vela-Acosta et al., 2002) and relies on small sample sizes, case study populations of patients, and/or a single avenue of injury (e.g., tractor accidents). There are some exceptions in the interrelated area of field sanitation practice. Ohayo-Mitoko et al. (1999) examined environmental determinants of pesticide exposure for Kenyan crop workers in several areas of the country, focusing on the types of pesticides used, protective devices available to the workers, and hygienic behavior. Protective devices in this context include access to gloves, boots, masks, and other equipment. Although hygienic behavior can vary from worker to worker and is largely unobservable, facilities available to the worker can affect behavior, such as the ability to wash or bathe after work. For the US case, Pena and Teather-Posadas (2018) documented what is known about field sanitation up to the recent period. These authors find that variables such as crop, task, and time period are predictors of access to various forms of field sanitation. This literature highlights some features of pesticide exposure and mitigation strategies, while there is a larger literature on pesticide-related health outcomes. A large subset of this health-based literature relates to fertility and pregnancy (e.g., Andersen et al., 2008; Curtis et al., 1999; de Cock et al., 1994; Nurminen, 1995). Of particular interest, Savitz et al. (1997) observed the effects of pesticide exposure of male workers on their offspring and the effects of female workers on their pregnancy in Canada. They found that handling pesticides and using specific chemicals increased the probability of having a miscarriage. McCauley et al. (2006) also addressed specific chemicals that have reproductive effects on female crop workers and noted that many of these chemicals are no longer used in US agriculture due to bans. While many of these chemicals have been banned for the safety of female crop workers, there also are documented negative effects on male workers' sperm causing birth defects.

In addition to these types of possible health effects of pesticide exposure related to reproduction, pesticides have also been linked to other health risks that directly impact current workers, including those associated with cancers (e.g., Bassil et al., 2007) and with mental health (e.g., Beseler et al., 2008; Beseler & Stallones, 2013; Stallones & Beseler, 2016).

Economic literature on health, productivity, and compensating wage differentials

Smith (1979) summarized the theory of compensating wage differentials in terms of numerous supply and demand characteristics interacting in terms of an equilibrium wage. In this framework, earnings are envisioned as a function of observed (and unobserved) productivity related characteristics, job-related characteristics (inclusive of risk and unpleasantness), and stochastic error (Duncan & Holmlund, 1983). Empirical applications related to compensating wage differentials are numerous and diverse in scope. Many relate to estimating the value of a statistical life for use in economic policy analysis and have interrelationships with workers' compensation programs (e.g., Arnould & Nichols, 1983; Dorsey & Walzer, 1983; Olson, 1981). Other empirical literature points out seeming contradictions to standard theoretical predictions associated with compensating wage differentials, suggesting the presence of noncompetitive rents in equilibrium (e.g., Bonhomme & Jolivet, 2009; Brown, 1980; Krueger & Summers, 1988). Other work adjusts for biases in standard empirical approaches to fine-tune compensating wage differential estimates (e.g., Gertler et al., 2005; Lavetti, 2020).

Correlations between poor health and low wages in various industries and populations are also well documented (e.g., Cai, 2009; Chirikos & Nestel, 1985; Contoyannis & Rice, 2001; Jäckle & Himmler, 2010; Thomas & Strauss, 1997; among others). As noted in the previous section, exposure to pesticides in agricultural work has been shown to have negative health outcomes on workers who are exposed. This exposure also can have negative effects on the economic and financial outcomes of workers, sometimes through the mechanism of work productivity (e.g., Loureiro, 2009).

Our reading of the literature suggests that the case of pesticides may be different from that of some other hazards because of the possibilities of direct productivity effects associated with the health impacts of exposures. This would be particularly true when wages are a precise function of productivity, such as in a piece rate payment scheme. The impacts of pesticide exposures then may work in the negative direction via the health/productivity effect and in the positive direction via the compensating wage differential associated with risk. It is then an empirical question as to whether these are offsetting or whether one of these impacts dominates.

A strand of literature more specific to agriculture addresses intersections between health concerns and economics that arise from modern farming practices. Some studies focus on demographic factor determinants of injuries and illnesses, while others focus on how the type of pay (hourly vs. piece rate) affects the rate of injury (e.g., Bender et al., 2012; Karttunen & Rautiainen, 2013; McCurdy et al., 2003). Of particular note are those studies that focus on more general health concerns of “migrant” workers who move between farm work locations during the agricultural season as this is an often overlooked and under-resourced population in the United States (Sakala, 1987; Villarejo, 2003). Sakala (1987) related these patterns to the farm work population having limited political organization and representation, while Villarejo (2003) cited data constraints and limited baseline information for agricultural workers.

From this review, we expect that pesticide exposure will have negative effects on worker wages due in part to negative health outcomes affecting worker productivity. Supportive of this, McCauley et al. (2006) found that pesticide exposure negatively affected productivity which can, in turn, affect worker compensation. Moretti (2000) provided an early treatment of compensating wage differentials in agriculture, though it relates differentials to the seasonality of work as opposed to health risk. Kandel and Donato (2009) discussed the topic of health risk with pesticides and its relationship to legal status but do not ultimately link to compensation and bargaining power. The authors found that “unauthorized legal status is associated with a reduced likelihood of handling pesticides or receiving training for pesticides” (p. 367). The authors related this finding to segmentation in the availability of “lousy” versus “skilled” jobs to those in various legal status groups.

Bargaining power in labor markets and relationships to legal status

The literature on union membership has documented how bargaining power can affect compensation outcomes (e.g., literature starting with Duncan & Stafford, 1980; Olson, 1981; Siebert & Wei, 1994; among others). Agriculture is characterized by a high percentage of undocumented workers compared to other industries. Our theoretical expectation, as in Kandel and Donato (2009), is that workers with reduced bargaining power would have lower expected wages, all else being equal, and that undocumented status may be an indicator of this bargaining power and its translation into wages. Our framing theory relates to the conceptualization of dual labor markets, labor market segmentation on various group indicators, labor market segregation, and labor market stratification (e.g., Arce & Segura, 2015; Dickens & Lang, 1988; Leontaridi, 1998; Reich et al., 1973; Taubman and Wachter 1986). When these types of market divisions exist, there may exist multiple equilibrium wages where legal workers in the more formal part of the agricultural labor market have higher bargaining power that translates into higher compensating wages than those received by otherwise similar, though undocumented, workers in the less formal segment of the agricultural labor market.

A final complexity relates to the prevalence of both piece rate and time rate payment schemes in the agricultural sector. The presence of both types of pay means that features of productivity are observable to different capacities across these earning structures. Our analysis of data detailing these contextual intricacies helps fill gaps in the current literature and is relevant for workforce and public policy initiatives since migrant crop workers are among the poorest working populations in the country and are crucial to meeting seasonal demands for the US agricultural sector.

THE HEALTH AND WAGES OF US CROP WORKERS

The National Agricultural Workers Survey

The National Agricultural Workers Survey (NAWS) is a large-scale survey of individual crop workers, their demographic characteristics including legal status, and their occupational health histories. Advantages of these data over other sources include detailed attention to farm work practice and direct surveying of whether or not workers are undocumented.1

Primary data used in this article are from the public access version of NAWS provided by the US Department of Labor through the Employment and Training Administration. The NAWS is both nationally and regionally representative of employed US crop workers, with the exception that this survey does not include workers in the H-2A Temporary Agricultural Program.2

[1]It should be noted that despite an estimated 92% response rate, the share of NAWS respondents who self-identify as undocumented may still be lower than the actual share (https://www.dol.gov/sites/dolgov/files/ETA/naws/pdfs/NAWS_Statistical_Methods_AKA_Supporting_Statement_Part_B.pdf).

[2]Sampling is from worksites instead of residences. NAWS uses 12 geographic regions. The public-use NAWS sample is collapsed into six regions and incorporates survey weights. Additional information and public access data are available from http://www.doleta.gov/agworker/naws.cfm.

With the availability of NAWS data, we can examine not only health and economic outcomes related to pesticide exposure but also examine demographic and economic determinants of exposure. Although the NAWS has been conducted in three seasons per year since 1989, the survey question pertaining to pesticide exposure that we exploit in this article was not asked until 2002. We therefore restrict to data from 2002 through 2016, which is the most recently available year of the public-use data. This leaves us with a sample size of 32,242 US crop workers. Arcury and Quandt (2007) concluded that there is a substantial need for new research on crop worker health and health services and particularly point to NAWS as a potential source of future data, which further supports the exercises that we present. Our work is a contribution and response to suggestions made by Arcury and Quandt (2007).

While previous literature using alternative data sources such as US labor force surveys and workers' compensation records has examined cost factors related to illness and exposure in US agriculture (e.g., Dosemeci et al., 2002; Douphrate et al., 2006; Leigh et al., 2001), there are advantages to using NAWS in order to increase understanding especially at the aggregate national level. It has been long-recognized in the economics literature that other large-scale household-level surveys are not representative of US crop workers (e.g., Gabbard et al., 1991) because of nonstandard housing situations and therefore due to a mismatch with traditional survey sample designs based on houses. Furthermore, the prevalence of undocumented work status creates further complexities and questions the completeness of workers' compensation information as claim activity is arguably very significantly a function of legal status. Overall, this is suggestive of a role for using specific crop worker data from NAWS in order to compare results with previous literature with those from a sample design based on the distinctive feature of agriculture and to derive further implications useful for cost–benefit studies of health and safety interventions. A primary feature of NAWS in comparison with other data sources is that legal status is directly observable, thus allowing for a statistical control (or stratification variable) of what has previously been an unobservable source of bias in many empirical models.

Arcury et al. (2010) described language and literacy barriers as important obstacles to overcome in the delivery of health and safety training programs for crop workers. As the NAWS provides detailed information on language acquisition, a variable for the ability to speak English is formulated and used.[3] We also include family structure variables indicating the presence of a spouse with the worker in the United States and the number of children. These variables may be correlated with propensities to engage in riskier work or not.

While it is likely that all crop workers around crops for which pesticides are used are exposed to some extent, the Environmental Protection Agency (EPA) indicates that primary exposures are via pesticide preparation (e.g., mixing and loading) and application as well as through picking of crops after these applications.[4]

[3]Respondents answer a survey question "How well do you speak English?" Responses of "not at all" and "a little" (in Spanish, "Nada" or "Un poco/No bien") are coded as the zero category, and responses of "somewhat" and "well" ("Algo/M as o menos" or "Bien/Muy bien") are coded as the one category to form the binary variable that is used.
[4] https://www.epa.gov/pesticide-worker-safety/how-epa-protects-workers-pesticide-risk

Summary statistics of pesticide exposure and worker outcomes

Figure 1a illustrates the proportion of US crop workers who indicate exposure to pesticides via loading, mixing, or applying pesticides.5 The total subsamples for those who are exposed by this definition and those who are not exposed by this definition are 6,369 and 25,873 workers, respectively. We see an increase in the amount of pesticide exposure reported over time in the NAWS survey question. The percentage reporting pesticide exposure through the activities of loading, mixing, or applying moves from about 10% of the sample to more than 15%. A visible spike occurs in 2005 before the trend begins to stabilize, hovering around 15% of the sample by the end of the available series. This pattern is consistent with the use of pesticides in the United States over this time. Fernandez-Cornejo et al. (2014), for example, showed that starting from 2005 to 2006, there was a substantial increase in the amount of pesticide use as measured by the active ingredients documented in that work (e.g., fungicides, herbicides, insecticides, and other types of pesticides).

Relative to many other industries, a high percentage of agricultural workers is paid by piece rate (i.e., wages based on output) instead of time rate (i.e., wages based on time input). "Hourly equivalent wages" are used for piece rate paid workers. The values for these wages are constructed by the US Department of Labor based on survey questions indicating how much a worker (and his or her crew if applicable) was paid on average for each unit of output (e.g., box, bin) and how many units were produced in an average day, along with the crew size information.6 Although the productivity output data (e.g., boxes packed) is suppressed in the public-use version of the data, we use these hourly-equivalent wages in the place of hourly wages for piece rate workers. We adjust these wages by the Consumer Price Index7 to create real wages in 2016 US dollars to match the endpoint of our data series.

Figure 1b illustrates average wages by the reported NAWS pesticide exposure variable over time. It becomes immediately clear that there is a sizeable gap between the average wages of those who are exposed to pesticides and the average wages of those who report having no pesticide exposure. Gaps between the two series are statistically and economically significant with those workers reporting exposure also reporting higher wages, a pattern suggestive of a compensating differential in pay. The pattern in panel (b) could theoretically be attributed to compensating wage differentials if, for example, workers are paid a premium for their willingness to work in a riskier occupational environment. However, it is again crucial to note that the series are unconditional on agricultural labor force composition, and it is highly likely that differences are also related to sorting of workers with more experience and tenure into more technical tasks such as those related to the handling of chemicals.8

[5]Since 2001, workers were asked: "In the last 12 months, have you loaded, mixed or applied pesticides?" From 1993 through 2000, workers were asked if they mixed or applied pesticides in the last 5 years. These two variables are not directly comparable given the differences in both scope and time frame of the survey questions. Figure 1 illustrates responses to the more recent question.

[6]These hourly-equivalent piece rate wages are then theoretically comparable with hourly rates reported by other workers though it is not known if and to what extent this construction introduces measurement error. In some specifications, we, therefore, analyze the piece rate subsample separately from the time rate paid one.

[7]We use the CPI-U current series from the Department of Labor's Bureau of Labor Statistics.

[8]The Environmental Protection Agency (EPA) requires a certification for an individual to be able to *supervise* others in handling pesticides (i.e., only one person needs to be certified in order to instruct/supervise others on the farm). It could be the case then that certain types of longer-term workers are sorted into these training programs. Unfortunately, NAWS information on training is limited. In the public-use data, there is one question available that asks about the timing of most recent instructions for pesticides. This

The question of actual exposure is even more complex as the fraction of crop workers exposed to pesticides is likely higher than that indicated in panel (a). The difference between reporting being exposed on the NAWS questionnaire and actually exposed may not be one of incidence, but rather of knowledge. Pesticides affect not just those who do the mixing and spraying but also those who work among them and those who pick to the extent that pesticides linger on crops and in the vicinity and can be transmitted via simple touch. This fact may not be well-translated to the workers. Furthermore, the transmission of pesticide residue can come in many forms including lack of handwashing (or improper handwashing), the use of a cellphone in the field, wiping one's face and neck while picking, or having dried and cracked hands.[9] This suggests that health effects may be both numerous and varied.[10]

We tabulate survey-weighted means and standard errors of major demographic and work-related characteristics by pesticide exposure. Analysis of these data suggests statistically significant and economically important differences for many demographic and work-related characteristics of US crop workers. As would be expected theoretically, this indicates that health and risk exposure do not affect workers equally, but instead, some types of workers are more vulnerable than others in systematic ways. Summary statistics also reveal that there may be a compensating differential paid to workers for their willingness to take occupational risks (e.g., higher wage in exchange for risk-taking in terms of pesticide exposure), and therefore trade-offs experienced by workers between health risk and economic success that are important for understanding the current and future health service needs of this population.

Demographics of our sample population support the assertion that specific roles on the farm drive contact with pesticides. Table 1 presents summary statistics (means and standard errors) for major variables overall (column [1]) and for the subsamples of exposed to pesticides and not exposed to pesticides (columns [2] and [3], respectively). Those who report that they loaded, mixed, or applied pesticides in the last year are classified as "exposed" and those who answered no to this question are our "not exposed" category. Exposed workers have higher wages on average ($11.52 per hour in comparison with $9.94 per hour on average in 2016 USD) and more frequent reports of having at least one diagnosed health condition (24.3% in comparison with 18.7%).

A further look at Table 1 reveals that those who are reporting having been exposed to pesticides are those who are older, have more years of formal education, have much more farm experience (16.9 vs. 11.5 years), and have longer tenure with the current employer (9.0 vs. 5.3 years). This points toward a story that it is the more experienced crop workers

question, however, was only available in the 1997–1998 and 1999–2000 waves of the survey. We, therefore, proxy for training using other available human capital indicators as specified in our empirical model.

[9]As the NAWS question pertains to loading, mixing, and direct application, the patterns here should be interpreted as a lower bound in terms of true pesticide exposure. Indeed, it may be more likely that everyone on the farm is exposed to pesticides in one manner or another.

[10]In Figure A1, we examine an analogous figure to that of Figure 1b where wages are replaced with an indicator for having at least one health condition (from a list consisting of asthma, diabetes, high blood pressure, tuberculosis, heart disease, urinary tract infections, and other diagnosed conditions). The *y*-axis can be interpreted as a fraction of workers with at least one diagnosed health conditions by year. Overall, those with pesticide exposures by our measure more frequently report health conditions than do others. This could be related to either direct relationships between pesticide exposure and particular conditions or could be related to relationships between exposure and seeing a doctor (who then may diagnose other conditions).

that are more likely to experience the type of exposures that the survey question documents. In contrast, Table A1 shows that a larger fraction of the nonexposed group (10.7% of that subsample in comparison with only 1.6% of the exposed) is paid piece rate wages and that these workers tend to be younger and to have less education, fewer years of farm work experience, and less tenure in terms of years with the current employer. These workers are also less likely to have a spouse or children in the United States, a pattern that may relate to the demand for compensating wage differentials when households are larger.

There are substantial differences in legal status across groups, with 30% of exposed workers reporting as undocumented in comparison with almost 53% of nonexposed workers reporting as undocumented. Undocumented workers may have lower exposures because of worker sorting into “types” of jobs if the availability of jobs differs for undocumented and documented workers. Alternately, undocumented workers may have less information about their true exposures, which would mean that our results should be interpreted in light of possible attenuation due to measurement error in the self-reported survey responses. There are also correlations with English language-speaking ability that parallel these patterns.

We expect true exposure to be more widespread as transmission may occur via other channels such as physically picking crops. Crop, task, and region display heterogeneous relationships with pesticides, which make sense due to variation in work requirements and in pesticide use across diverse farm operations. Fruit and vegetable crops are also more common responses for crop type in the not exposed category though this is likely due to the scale of these operations and the numbers of workers involved since pesticides are used for many of these crops.

Regional variation based on pesticide exposure by this definition also is limited. The only noticeable exceptions are California (reported for 37.2% of crop workers who are not exposed to pesticides in Table 1). The other exception is the Southwest, which has a larger gap between its representation in the exposed (12.8%) category and the not exposed (6.9%) category. A similar gap exists in the Southeast, with the level of exposed category at 17.2% and not exposed category at 11.0%.

We reproduce these summary statistics by stratifying further by pay basis and legal status in Tables A1 and A2, respectively. Consistent with past literature, piece rate workers have higher wages than hourly workers in Table A1. Wages are similar across the exposure categories for piece rate workers but are higher for exposed workers in the hourly category. Health condition reports are highest for this subpopulation. When dividing into undocumented and documented subsamples (Table A2), we note that wages are higher for documented workers as expected, given both differences in bargaining power and differences in the composition of worker features across the undocumented and documented categories. The fraction of workers who report health conditions, however, is lower for workers with and without pesticide exposure in the undocumented category. This also could be related to compositional differences, such as younger age for this group on average. Within legal status category (undocumented and documented, respectively), we see higher wages and higher reports of health conditions for exposed workers relative to unexposed ones.

RELATIONSHIPS BETWEEN PESTICIDE EXPOSURES AND WAGES

Our key statistical methodology is parametric multivariate regression analysis to evaluate relationships between pesticide exposure and both health and economic outcomes such as productivity and earnings. The basic econometric framework takes the general form:

$$y_i = \alpha \text{ pesticide}_i + X_i\beta + \varepsilon_i, \qquad (1)$$

where the dependent variable y_i is firstly the probability of negative health conditions $P\ (health\ condition)_i$ and secondly is $ln(wages)_i$, which is the natural logarithmic hourly-equivalent wage rate as previously defined. Models are run aggregately across workers of all payment types and separately for workers under piece rate and time rate payment schemes.

Ideally, we would examine direct productivity as a dependent variable in addition to wages. Unfortunately, the productivity measures that are available for the subset of piece rate paid workers are suppressed in the current public-use version of the data set. Still, we know that physical productivity is more highly correlated to piece rate wages than to time rate wages. We separate types of pay structure in order to gain intuition on productivity effects indirectly in many of our modeling specifications.[11] We also examine subsamples of workers based on whether they report being documented (the US born, naturalized citizens, Green Card holders, and those with other work authorization) or undocumented, given our hypotheses about differences in the agency across these groups.

The variable $pesticide_i$ denotes our risk exposure. As explained in the data description, this variable is based on self-reported pesticide exposures, which we interpret as having measurement error in that it is an understatement of actual exposures. This has the implication that the estimated α should be interpreted as a lower bound estimate of the impact of pesticide exposure.

The vector X_i includes nativity, legal status,[12] and other general demographic and work-related characteristics such as gender, age, education, experience, tenure with current employer, crop, task, geographic region, and survey year.

Because we are interested in the effects of differences in bargaining power as proxied by observable differences in legal status, we extend Equation (1) for the determination of wages to include interactions between pesticides and the various immigrant legal status categories. We, therefore also estimate equations of the form:

$$\begin{aligned} \ln\left(\text{wages}\right)_i = {} & \alpha\ pesticide_i + \beta_1 pesticide_i * natcitizen_i + \beta_2 pesticide_i \\ & * greencardplus_i + \beta_3 pesticide_i \\ & * undocumented_i + X_i\beta + \varepsilon_i \end{aligned} \qquad (2)$$

[11] Approximately 95% of workers in the survey are observed in either hourly or piece rate payment schemes. The remaining workers report “combination” hourly and piece rate pay or salary pay. We have excluded these categories from our subsample analysis by payment structure due to sample size.

[12] Legal status results for the undocumented variable should be considered lower bounds as some errors in variables bias may be introduced, thus attenuating coefficients toward zero. Workers who are US born, who have naturalized citizenship, who have Green Cards or other work authorization, and undocumented workers are identified in NAWS.

We are interested in the coefficients on the pesticide-legal status interaction terms and hypothesize that compensating wage differentials will be increasing in the legal status category ranked from least status (undocumented) to most (naturalized citizen included in the regression, and the US born citizens included as the base category). An intermediate legal status category is that of those with Green Cards or other work authorization.

RESULTS

Associations between pesticide exposure and health by pay basis and legal status

Determinants of having diagnosed health conditions from probit regression are shown in Table 2, and marginal effects of the probability of reporting at least one health condition are reported. In terms of individual characteristics, age (across samples) and farm experience (for piece rate workers) have a statistically significant relationship with reporting diagnosed health issues on this survey at the 1% significance level. Crop workers coming from Mexico are less likely to report the health conditions listed.

As expected, exposure to pesticides while on the job has a positive relationship with having a health condition overall (columns [1] and [2]), indicating that exposed workers, all else being equal, are more likely to report negative health status. In our fully specified estimation, which controls for individual characteristics, type of farm work (both crop and task), region, and time, pesticide exposure increases the probability of having a health issue by 2.6 percentage points (column [2]). Results for hourly workers are similar (columns [5] and [6]), but we find no significance on pesticide exposure on health outcomes for the subsample of piece rate workers (columns [3] and [4]). This could be a result of a low proportion of the sample being paid piece rate (and therefore higher standard errors) or because of differences in these types of jobs and their lower propensities for exposure, which may translate into differences in health outcomes.

Columns (7) and (8) provide estimations on the subsample of undocumented workers, while columns (9) and (10) do the same for documented workers. Pesticide exposure increases the likelihood of having a health issue by 4.3 percentage points for undocumented workers when controlling for type of harvest, region, and time (column [8] of Table 2). With the same controls, there is no significant impact of pesticide exposure on health outcomes (column [10]) for documented workers though the estimated sign of the coefficient remains positive. These differences motivate the continued examination of legal status while considering the presence of a wage premium for risk, though differences across these groups are smaller for wage as an outcome (Table 3). We interpret these estimates as lower bounds of the true impacts since pesticide exposure should be negatively correlated with the estimated regression error if reported pesticide exposure is an understatement of actual exposure.[13]

[13]Our results are robust to the inclusion of a variable for employer type (i.e., farm labor contractor vs. grower hiring workers directly). Due to high correlations between this variable and the other work-related characteristics, which we do control for directly in this article, we have not included this variable in the final specifications.

Associations between pesticide exposure and wages by pay basis and legal status

Table 3 provides the Ordinary Least Squares results for the association between pesticide exposure (in addition to individual characteristics, work-related characteristics, and regional location) and wages. The dependent variable in this case is the natural log of real wages. As expected, there are multiple individual-level characteristics that correlate with the wages earned by the crop worker, such as experience, age, and education. As consistent with the literature in labor economics across industries, work-related experience, age, and education are positively correlated with wages.

Overall, crop workers who are exposed to pesticides are likely to earn more in wages (columns (1) and (2)). This is consistent with the existence of a compensating wage differential associated with pesticide exposures. When controlling for type of farming, region, and time, pesticide exposure is associated with wages that are 7.0% higher on average, all else being equal (column (2)). Pesticide exposure has no significant relationship, however, with wages for crop workers being paid per unit of harvest (piece rate), but does have a positive significant relationship with hourly-paid workers (results in columns (3) through (6)). For hourly workers, pesticide exposure is associated with higher wages of nearly 7% (like for the aggregate results) when controlling for harvest type, region, and including time fixed effects (column (6)). When looking at the legal status of the worker, both documented and undocumented workers see a statistically significant positive increase in wages when exposed to pesticides. However, although workers in either status experience a wage premium when working with pesticides, the premium is *larger* for documented workers than for undocumented workers. Documented workers see almost 8% higher wages compared to undocumented workers with a <5% premium. Since these regressions control for a wide variety of individual and work-related characteristics, this difference is striking from a distributional perspective.

Before discussing implications, we further explore this result in Table 4, where the interaction terms associated with exposures and naturalized citizens, Green Card holders and other work authorization, and undocumented workers, respectively, are interpretable relative to any compensating wage differentials experienced by US born workers. Our estimations follow the logic in Equation (2).

In the overall sample inclusive of both piece rate and hourly workers, the baseline pesticide exposure variable (for US born workers) is positive and statistically significant, consistent with the compensating wage differential that we previously discussed. The interaction term between pesticide exposure and naturalized citizen status is insignificantly different from the base of US born workers. This would be expected if these types of workers are indistinguishable in terms of bargaining power with employers due to both having citizenship. This is also evident in terms of the insignificant coefficient on the dummy variable for naturalized citizens (relative to the excluded US born category).

Interaction terms with Green Card holder/other work authorization status and with undocumented status, respectively, are positive and in the expected direction. To assess the estimated positive sign and magnitude of margin impacts of legal status, we simultaneously consider the negative coefficients on the dummy variables for Green Card and other work authorization and for undocumented status. The positive interaction term offsets the negative coefficient for Green Card and other work authorization, though only partially offsets the coefficient on the dummy for undocumented status.

The hourly subsample results (columns (5) and (6)) are quite similar qualitatively to those for the full sample (columns (1) and (2)). These patterns, however, break down in the piece rate subsample. Interestingly, the coefficient on pesticides alone is negative and significant in the piece rate subsample regressions when these interaction terms are included (columns (3) and (4) of Table 4). In addition, the coefficient on the interaction term between pesticides and naturalized citizens is positive and significant, and that on naturalized citizens alone is negative. We note that the compositions of worker characteristics in the piece rate versus hourly worker sub-samples are quite different, with much lower percentages of both naturalized citizens and undocumented workers in piece rate positions (Table 1). We also note that the exposed piece rate subsample is very small (Table A1), and therefore readers should interpret this subsample with caution.

CONCLUSIONS, CAVEATS, AND POLICY IMPLICATIONS

Pesticides, although potentially harmful to the workers handling them, can increase the quality and safety of agricultural goods. Due to added benefits of using pesticides in agricultural goods, many crop workers are exposed every day, and studying pesticide exposure is important, in part due to significant health effects on crop workers handling these chemicals. This article examined these health effects and the related economics. Our findings are consistent with the presence of compensating wage differentials for pesticide handling, or payment to offset these risks, within agricultural worker populations.

We find, however, that undocumented workers receive a smaller wage premium for pesticide exposure than their documented counterparts, and that they also are more likely to have health issues if exposed to pesticides than documented workers. This suggests that undocumented workers in agriculture may make sacrifices in both their economic and physical health as a result of limited work options coupled with lower bargaining power and agency and that compensating wage differentials for risk are insufficient to outweigh expected health outcomes on average. A complementary result is that this pattern is observed largely with hourly employees rather than piece rate employees. Since piece rate pay schemes are a function of observable output as opposed to factors including more unobservable bargaining power, their compensation structure may provide more opportunities for workers of all legal statuses to receive payment more commensurate with their work and the extent of physical risk embodied in that work. Piece rate pay, however, has become *less* frequently observed over time (Pena, 2010a).

Bargaining power and agency differences associated with legal status then provide a mechanism that is consistent with our results, as is the possibility of more explicit discriminatory practices in the wage-setting of some workers that is amplified when these workers are paid an hourly wage as opposed to a piece rate wage that is more clearly linked to productivity. Since negative health outcomes for relatively poor workers are socially costly, renewed promotion of piece rate pay structures as a compensation policy could be seen as one strategy to reduce public health costs since pass-through of costs to public health systems is lower when workers are paid higher wages. This type of a change could potentially impact the distributional surplus between employers and employees in equilibrium, as well as the relative fractions of workers negatively impacted in their health. The predicted overall effectiveness of the type of intervention, however, would be necessarily dependent on a complete assessment of all costs and benefits associated with piece rate pay structures.

Our modeling is based on an idea that a piece rate wage structure, to at least some extent, gives all workers, regardless of their immigration status, the opportunity to evaluate whether pay is commensurate to the risks inherent in the work. Fully evaluating the promotion of piece rates, however, requires a deeper consideration of selection and sorting into piece rate work. The summary statistics in Table 1 suggest that a majority of piece rate workers are engaged in harvesting, a stage of production when pesticides as less likely to be applied. While we do control for agricultural work tasks in the regression analysis, our finding of limited impacts of pesticide exposure on health conditions or wages for piece rate workers in Tables 2 and 3 still may partially relate to the nature of work as opposed to piece rate structure itself. Our findings suggest that those stages of production where pesticides are most likely to be applied then are the most critical for policy interventions.

Our results also have implications for the importance of greater general compensation oversight if fair and equitable wages are an objective of policy in the United States. Our results, for example, also have relevance pertaining to minimum wage enforcement. Fan and Pena (2019) documented incomplete minimum wage enforcement in agriculture, with the largest gaps appearing for undocumented workers. This is suggestive of space to increase labor policy enforcement as a method to increase worker compensation inherent in agricultural work. Kandilov and Kandilov (2020), however, found that minimum wage enforcement may discourage seasonal hiring of farmworkers and, over the long term, encourages shifts to more capital-intensive forms of production. This again alludes to the need for a more complete assessment weighing all projected policy implications.

In addition to economic-based interventions, an alternate, perhaps more feasible, shorter-term policy intervention would be targeting of occupational health resources (including personal protective equipment [PPE] and enhanced education on safety strategies to minimize health risks associated with pesticide exposure) toward particular crop workers with increased risk factors (e.g., those who are undocumented) since the findings in this article suggest that these workers experience a higher likelihood that pesticide exposure adversely affects their health. This is particularly important at the time of this writing as COVID-19 is not yet fully controlled in farm work populations.

Further understanding of determinants of pesticide exposure, of their impacts on health outcomes, and of health outcome effects on productivity and wages remains important for strategic planning for future workforce investments and for occupational safety and health policy. Our modeling approach was to focus on the association between pesticide exposures and worker outcomes in terms of their physical and economic health. A caveat to our analysis is that we did not directly model what determines pesticide exposures in the first place.[14] We thus argue that our results provide one input into decision-making regarding the targeting of occupational health policies by indicating how workers may be differentially impacted by existing workplace relationships.

A final caveat is that the pesticide variable that we use does not capture all possible exposures, and there may be information asymmetry within the worker population regarding the risk that is unobservable to us. Although we have interpreted our point estimates as lower bounds of exposure impacts, this data complexity points out a limitation of existing information and suggests that further research into the nature of exposures is necessary.

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[14]Kandel and Donato (2009) provide a complementary study.

Appendix

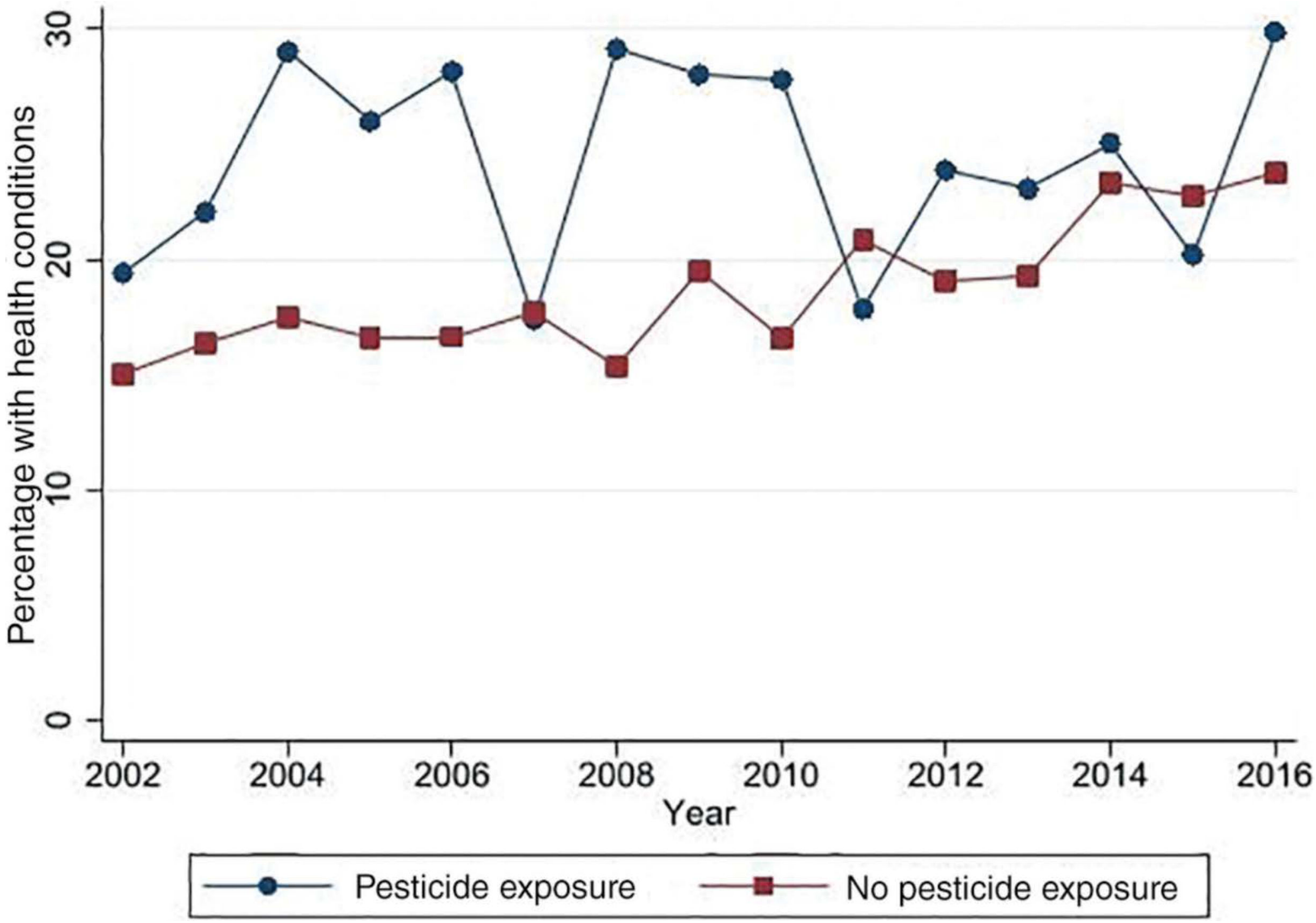

FIGURE A1.

Percentage of workers with diagnosed health conditions by pesticide exposure over time

Source: NAWS and authors' calculations

TABLE A1.

Means of demographic and work-related characteristics, by pesticide exposure and pay basis

Piece rate				**Hourly**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	**Overall**	**Exposed**	**Not exposed**	**Overall**	**Exposed**	**Not exposed**
Wage (2016 USD)	11.35	11.27	11.35	9.701	10.84	9.497
	(0.170)	(1.024)	(0.173)	(0.0250)	(0.0800)	(0.0251)
Female	0.208	0.189	0.209	0.271	0.0834	0.305
	(0.0153)	(0.0929)	(0.0155)	(0.00617)	(0.00849)	(0.00699)
Age (years)	34.23	33.71	34.24	36.14	37.80	35.84
	(0.375)	(1.799)	(0.382)	(0.174)	(0.379)	(0.193)
Any health condition	0.124	0.163	0.123	0.199	0.231	0.193

Piece rate				Hourly		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Overall	Exposed	Not exposed	Overall	Exposed	Not exposed
	(0.00966)	(0.0794)	(0.00969)	(0.00499)	(0.0109)	(0.00555)
Education (years)	6.432	6.477	6.430	8.078	8.841	7.942
	(0.152)	(0.534)	(0.155)	(0.0535)	(0.110)	(0.0597)
Farm experience (years)	11.01	14.42	10.92	12.05	16.14	11.32
	(0.331)	(2.012)	(0.333)	(0.136)	(0.318)	(0.147)
Tenure (years)	4.012	6.411	3.950	5.792	8.565	5.296
	(0.130)	(1.419)	(0.128)	(0.0787)	(0.208)	(0.0840)
Has spouse in the United States	0.395	0.479	0.392	0.471	0.561	0.455
	(0.0168)	(0.109)	(0.0170)	(0.00645)	(0.0140)	(0.00718)
Children (number)	0.832	1.172	0.823	0.894	1.060	0.865
	(0.0472)	(0.346)	(0.0477)	(0.0154)	(0.0359)	(0.0170)
Naturalized citizen	0.0140	0.0584	0.0128	0.0416	0.0541	0.0394
	(0.00286)	(0.0474)	(0.00267)	(0.00212)	(0.00447)	(0.00237)
Green Card or other author	0.238	0.250	0.238	0.213	0.229	0.210
	(0.0136)	(0.112)	(0.0136)	(0.00493)	(0.0104)	(0.00551)
Undocumented	0.706	0.658	0.707	0.485	0.325	0.513
	(0.0145)	(0.113)	(0.0145)	(0.00646)	(0.0119)	(0.00723)
Speaks English	0.133	0.0931	0.134	0.378	0.543	0.349
	(0.0117)	(0.0565)	(0.0119)	(0.00651)	(0.0133)	(0.00721)
From Mexico	0.908	0.956	0.906	0.680	0.568	0.700
	(0.0108)	(0.0332)	(0.0110)	(0.00641)	(0.0143)	(0.00706)
Field crops	0.0219	0.0102	0.0222	0.144	0.275	0.121
	(0.00569)	(0.00681)	(0.00583)	(0.00434)	(0.0126)	(0.00452)
Fruit crops	0.755	0.783	0.754	0.289	0.306	0.286
	(0.0141)	(0.0859)	(0.0143)	(0.00582)	(0.0115)	(0.00656)
Horticulture	0.00934	0.0107	0.00931	0.247	0.235	0.249
	(0.00190)	(0.00894)	(0.00194)	(0.00582)	(0.0131)	(0.00645)
Vegetables	0.211	0.194	0.212	0.273	0.125	0.300
	(0.0133)	(0.0852)	(0.0135)	(0.00581)	(0.00917)	(0.00660)
Misc. crop	0.00263	0.00274	0.00263	0.0465	0.0591	0.0442
	(0.00108)	(0.00282)	(0.00111)	(0.00227)	(0.00565)	(0.00247)
Pre-harvest	0.0300	0.0151	0.0303	0.283	0.232	0.292
	(0.00391)	(0.00953)	(0.00400)	(0.00627)	(0.0108)	(0.00709)
Harvest	0.745	0.646	0.747	0.161	0.0914	0.174
	(0.0153)	(0.100)	(0.0155)	(0.00429)	(0.00724)	(0.00489)
Post-harvest	0.0611	0	0.0627	0.185	0.0784	0.204
	(0.00851)	(0)	(0.00872)	(0.00537)	(0.00803)	(0.00612)
Semi-skill	0.156	0.329	0.151	0.249	0.460	0.211
	(0.0136)	(0.0995)	(0.0137)	(0.00515)	(0.0139)	(0.00524)
Supervisor or other task	0.00835	0.00956	0.00832	0.122	0.138	0.119

Piece rate				Hourly		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Overall	Exposed	Not exposed	Overall	Exposed	Not exposed
	(0.00263)	(0.00525)	(0.00270)	(0.00407)	(0.00817)	(0.00457)
California	0.485	0.466	0.486	0.345	0.269	0.358
	(0.0168)	(0.112)	(0.0171)	(0.00572)	(0.0102)	(0.00649)
East	0.0904	0.0295	0.0919	0.143	0.119	0.147
	(0.0105)	(0.0157)	(0.0107)	(0.00426)	(0.00896)	(0.00476)
Southeast	0.184	0.0506	0.187	0.107	0.166	0.0968
	(0.0125)	(0.0226)	(0.0128)	(0.00382)	(0.0117)	(0.00394)
Midwest	0.0436	0.0376	0.0437	0.182	0.165	0.185
	(0.00547)	(0.0191)	(0.00558)	(0.00646)	(0.0123)	(0.00728)
Southwest	0.0260	0.0310	0.0259	0.0807	0.127	0.0724
	(0.00493)	(0.0310)	(0.00500)	(0.00327)	(0.00902)	(0.00348)
Northwest	0.171	0.386	0.166	0.143	0.155	0.141
	(0.0169)	(0.106)	(0.0171)	(0.00432)	(0.00932)	(0.00481)
Observations	2725	67	2658	27,369	5500	21,869

Source: NAWS and author calculations, standard errors in parentheses.

TABLE A2.

Means of demographic and work-related characteristics, by pesticide exposure and legal status

Undocumented				Documented		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Overall	Exposed	Not exposed	Overall	Exposed	Not exposed
Wage (2016 USD)	9.577	10.33	9.502	10.76	12.04	10.43
	(0.0384)	(0.115)	(0.0403)	(0.0489)	(0.127)	(0.0507)
Piece rate	0.134	0.0345	0.144	0.0542	0.00772	0.0663
	(0.00532)	(0.00824)	(0.00579)	(0.00297)	(0.00333)	(0.00366)
Hourly	0.834	0.928	0.825	0.860	0.831	0.868
	(0.00570)	(0.0115)	(0.00618)	(0.00519)	(0.0105)	(0.00593)
Female	0.243	0.0739	0.261	0.274	0.0817	0.323
	(0.00763)	(0.0116)	(0.00825)	(0.00806)	(0.00969)	(0.00957)
Age (years)	32.11	34.15	31.90	40.08	40.07	40.09
	(0.166)	(0.335)	(0.179)	(0.256)	(0.487)	(0.296)
Any health condition	0.118	0.148	0.115	0.270	0.283	0.267
	(0.00501)	(0.0139)	(0.00533)	(0.00715)	(0.0135)	(0.00830)
Education (years)	6.780	6.977	6.760	9.176	9.945	8.977
	(0.0611)	(0.126)	(0.0660)	(0.0674)	(0.114)	(0.0796)
Farm experience (years)	7.986	10.97	7.686	16.49	19.39	15.74
	(0.102)	(0.258)	(0.108)	(0.214)	(0.417)	(0.245)
Tenure (years)	3.876	5.991	3.663	7.734	10.33	7.061
	(0.0567)	(0.176)	(0.0587)	(0.127)	(0.284)	(0.140)

Undocumented				**Documented**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	**Overall**	**Exposed**	**Not exposed**	**Overall**	**Exposed**	**Not exposed**
Has spouse in the United States	0.401	0.539	0.387	0.541	0.596	0.526
	(0.00822)	(0.0197)	(0.00884)	(0.00852)	(0.0165)	(0.00982)
Children (number)	0.856	1.182	0.823	0.939	1.004	0.922
	(0.0191)	(0.0626)	(0.0199)	(0.0211)	(0.0378)	(0.0246)
Speaks English	0.106	0.193	0.0972	0.620	0.736	0.590
	(0.00528)	(0.0161)	(0.00557)	(0.00771)	(0.0121)	(0.00917)
From Mexico	0.929	0.910	0.931	0.460	0.381	0.481
	(0.00456)	(0.0138)	(0.00482)	(0.00820)	(0.0143)	(0.00963)
Field crops	0.0740	0.128	0.0686	0.212	0.371	0.171
	(0.00381)	(0.0135)	(0.00395)	(0.00656)	(0.0152)	(0.00710)
Fruit crops	0.413	0.422	0.412	0.258	0.243	0.263
	(0.00811)	(0.0196)	(0.00871)	(0.00708)	(0.0117)	(0.00837)
Horticulture	0.184	0.250	0.177	0.247	0.204	0.259
	(0.00621)	(0.0175)	(0.00659)	(0.00788)	(0.0151)	(0.00912)
Vegetables	0.293	0.134	0.309	0.234	0.127	0.261
	(0.00757)	(0.0130)	(0.00819)	(0.00704)	(0.0109)	(0.00836)
Misc. crop	0.0360	0.0657	0.0330	0.0483	0.0552	0.0465
	(0.00222)	(0.00817)	(0.00229)	(0.00321)	(0.00653)	(0.00367)
Pre-harvest	0.264	0.260	0.265	0.239	0.206	0.247
	(0.00819)	(0.0173)	(0.00885)	(0.00732)	(0.0117)	(0.00868)
Harvest	0.282	0.113	0.299	0.171	0.104	0.188
	(0.00673)	(0.0123)	(0.00732)	(0.00624)	(0.00930)	(0.00745)
Post-harvest	0.153	0.0682	0.162	0.184	0.0759	0.212
	(0.00636)	(0.00913)	(0.00692)	(0.00696)	(0.00937)	(0.00833)
Semi-skill	0.207	0.424	0.185	0.276	0.475	0.225
	(0.00573)	(0.0197)	(0.00583)	(0.00721)	(0.0160)	(0.00760)
Supervisor or other task	0.0929	0.135	0.0887	0.130	0.139	0.127
	(0.00457)	(0.0136)	(0.00484)	(0.00541)	(0.00914)	(0.00640)
California	0.438	0.345	0.447	0.274	0.215	0.290
	(0.00790)	(0.0178)	(0.00852)	(0.00662)	(0.0103)	(0.00789)
East	0.129	0.0978	0.132	0.148	0.134	0.152
	(0.00512)	(0.0113)	(0.00552)	(0.00604)	(0.0108)	(0.00706)
Southeast	0.120	0.167	0.115	0.118	0.174	0.103
	(0.00465)	(0.0157)	(0.00485)	(0.00533)	(0.0134)	(0.00567)
Midwest	0.102	0.0455	0.108	0.229	0.221	0.232
	(0.00761)	(0.0104)	(0.00827)	(0.00825)	(0.0150)	(0.00963)
Southwest	0.0503	0.0982	0.0454	0.105	0.140	0.0956
	(0.00331)	(0.0116)	(0.00344)	(0.00468)	(0.0105)	(0.00521)
Northwest	0.161	0.246	0.152	0.125	0.117	0.128
	(0.00598)	(0.0178)	(0.00632)	(0.00546)	(0.00930)	(0.00644)

Undocumented				Documented		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Overall**	**Exposed**	**Not exposed**	**Overall**	**Exposed**	**Not exposed**
Observations	16,191	2163	14,028	16,050	4205	11,845

Source: NAWS and author calculations, standard errors in parentheses.

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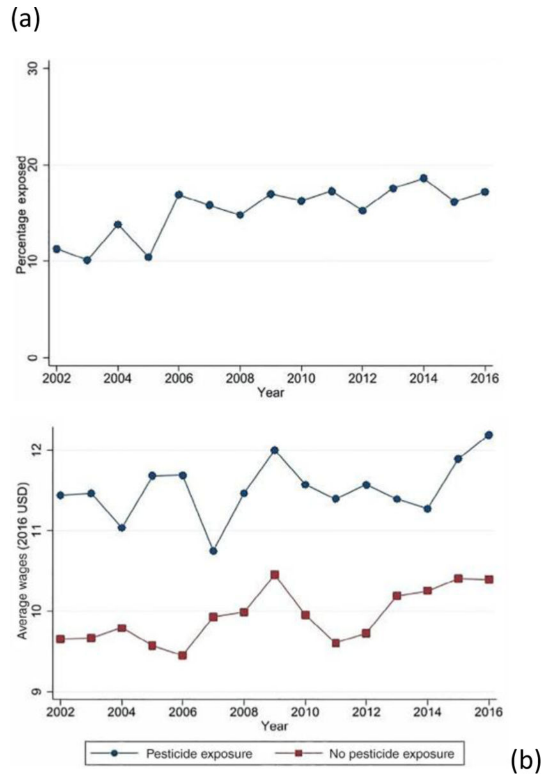

Figure 1. Pesticide exposure and wages over time.

(a) Percentage of crop workers with pesticide exposure.

(b) Average wages by pesticide exposure *Source:* NAWS and authors' calculations

TABLE 1

Means of demographic and work-related characteristics of crop workers by pesticide exposure

Variables	(1) Overall	(2) Exposed	(3) Not exposed
Wage (2016 USD)	10.18	11.52	9.942
	(0.0318)	(0.0957)	(0.0325)
Piece rate	0.0935	0.0158	0.107
	(0.00307)	(0.00342)	(0.00355)
Hourly	0.847	0.860	0.845
	(0.00386)	(0.00807)	(0.00431)
Female	0.259	0.0794	0.290
	(0.00556)	(0.00762)	(0.00630)
Age (years)	36.16	38.29	35.78
	(0.155)	(0.348)	(0.172)
Any health condition	0.195	0.243	0.187
	(0.00445)	(0.0103)	(0.00490)
Education (years)	7.996	9.050	7.810
	(0.0494)	(0.0991)	(0.0552)
Farm experience (years)	12.30	16.85	11.50
	(0.125)	(0.298)	(0.134)
Tenure (years)	5.834	9.022	5.274
	(0.0718)	(0.204)	(0.0749)
Has spouse in the United States	0.472	0.579	0.453
	(0.00583)	(0.0128)	(0.00648)
Children (number)	0.898	1.058	0.870
	(0.0142)	(0.0328)	(0.0157)
Naturalized citizen	0.0408	0.0581	0.0377
	(0.00188)	(0.00431)	(0.00208)
Green Card or other author	0.215	0.219	0.214
	(0.00448)	(0.00942)	(0.00500)
Undocumented	0.493	0.301	0.526
	(0.00585)	(0.0107)	(0.00653)
Speaks English	0.367	0.572	0.331
	(0.00587)	(0.0120)	(0.00648)
From Mexico	0.691	0.541	0.718
	(0.00578)	(0.0129)	(0.00634)
Field crops	0.144	0.298	0.117
	(0.00389)	(0.0116)	(0.00401)
Fruit crops	0.335	0.297	0.341
	(0.00550)	(0.0105)	(0.00618)
Horticulture	0.216	0.218	0.216
	(0.00508)	(0.0118)	(0.00561)
Vegetables	0.263	0.129	0.286

Variables	(1) Overall	(2) Exposed	(3) Not exposed
	(0.00518)	(0.00858)	(0.00587)
Misc. crop	0.0422	0.0583	0.0394
	(0.00197)	(0.00519)	(0.00212)
Pre-harvest	0.252	0.222	0.257
	(0.00550)	(0.00972)	(0.00622)
Harvest	0.226	0.107	0.246
	(0.00457)	(0.00747)	(0.00521)
Post-harvest	0.169	0.0736	0.186
	(0.00472)	(0.00711)	(0.00538)
Semi-skill	0.242	0.459	0.204
	(0.00466)	(0.0127)	(0.00474)
Supervisor or other task	0.112	0.137	0.107
	(0.00356)	(0.00758)	(0.00397)
California	0.355	0.254	0.372
	(0.00524)	(0.00922)	(0.00593)
East	0.139	0.123	0.142
	(0.00397)	(0.00832)	(0.00444)
Southeast	0.119	0.172	0.110
	(0.00354)	(0.0105)	(0.00370)
Midwest	0.167	0.168	0.167
	(0.00565)	(0.0113)	(0.00634)
Southwest	0.0779	0.128	0.0692
	(0.00289)	(0.00811)	(0.00307)
Northwest	0.143	0.156	0.141
	(0.00405)	(0.00864)	(0.00452)
Observations	32,242	6369	25,873

Source: NAWS and author calculations, standard errors in parentheses.

TABLE 2

Probit relationships between pesticide exposure and probability of health conditions, by pay basis and legal status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	**All**	**All**	**Piece rate**	**Piece rate**	**Hourly**	**Hourly**	**Undocumented**	**Undocumented**	**Documented**	**Document**
Pesticides	0.0286***	0.0262**	0.0125	0.00779	0.0288**	0.0272**	0.0362**	0.0426***	0.0242	0.0193
	(0.0109)	(0.0112)	(0.0678)	(0.0591)	(0.0119)	(0.0122)	(0.0142)	(0.0151)	(0.0162)	(0.0165)
Female	0.104***	0.102***	0.0966***	0.0781***	0.103***	0.104***	0.111***	0.106***	0.0905***	0.0903***
	(0.0124)	(0.0124)	(0.0301)	(0.0279)	(0.0134)	(0.0135)	(0.0147)	(0.0144)	(0.0194)	(0.0193)
Age (years)	0.00610***	0.00612***	0.00295***	0.00325***	0.00641***	0.00641***	0.00433***	0.00425***	0.00779***	0.00797**
	(0.000499)	(0.000491)	(0.000924)	(0.000885)	(0.000554)	(0.000544)	(0.000512)	(0.000492)	(0.000824)	(0.000833
Education (years)	0.000152	5.46e-05	0.00279	0.00237	0.000648	0.000411	0.00151	0.00121	0.00202	0.00190
	(0.00140)	(0.00140)	(0.00306)	(0.00281)	(0.00157)	(0.00158)	(0.00136)	(0.00134)	(0.00252)	(0.00248)
Farm experience (years)	0.000713	0.000568	0.00374***	0.00376***	0.000438	0.000273	2.23e–05	3.62e–05	0.000708	0.000598
	(0.000593)	(0.000596)	(0.00130)	(0.00122)	(0.000662)	(0.000663)	(0.000758)	(0.000763)	(0.000915)	(0.000936
Tenure (years)	0.000817	0.000828	0.000741	0.00142	0.000653	0.000697	0.00248**	0.00268**	0.000537	0.000519
	(0.000629)	(0.000626)	(0.00185)	(0.00177)	(0.000719)	(0.000713)	(0.00108)	(0.00106)	(0.000874)	(0.000868
Has spouse in the United States	0.0361***	0.0352***	0.0474**	0.0317	0.0346***	0.0346***	0.0270**	0.0287**	0.0420**	0.0377**
	(0.0105)	(0.0105)	(0.0230)	(0.0213)	(0.0119)	(0.0118)	(0.0119)	(0.0115)	(0.0169)	(0.0168)
Children (number)	0.00367	0.00421	0.0139*	0.0121*	0.00431	0.00485	0.00454	0.00511	0.00483	0.00528
	(0.00361)	(0.00359)	(0.00781)	(0.00727)	(0.00402)	(0.00398)	(0.00410)	(0.00400)	(0.00596)	(0.00589)
Naturalized citizen	0.0642**	0.0558*	0.0464	0.0529	0.0790**	0.0728**			0.0771*	0.0753*
	(0.0294)	(0.0293)	(0.0487)	(0.0406)	(0.0330)	(0.0331)			(0.0413)	(0.0417)
Green Card or other author	0.00829	0.0149	0.0326	0.0399	0.00581	0.000178			0.0147	0.0167
	(0.0234)	(0.0231)	(0.0498)	(0.0429)	(0.0263)	(0.0262)			(0.0384)	(0.0382)
Undocumented	0.0445*	0.0512**	0.0423	0.0299	0.0362	0.0421				
	(0.0244)	(0.0248)	(0.0638)	(0.0580)	(0.0266)	(0.0271)				
Speaks English	0.0176	0.0168	0.0408*	0.0344	0.0221	0.0211	0.00748	0.00583	0.0254	0.0237
	(0.0135)	(0.0134)	(0.0218)	(0.0220)	(0.0151)	(0.0148)	(0.0164)	(0.0149)	(0.0202)	(0.0202)
From Mexico	0.0591***	0.0575***	0.0707	0.0830	0.0622***	0.0623***	0.0414*	0.0455*	0.0764**	0.0815**
	(0.0204)	(0.0215)	(0.0613)	(0.0581)	(0.0220)	(0.0234)	(0.0236)	(0.0239)	(0.0330)	(0.0341)
Crop, task, year and region fixed effects?	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	32,936	32,936	2986	2986	27,522	27,522	16,461	16,461	16,474	16,474

Source: NAWS and author calculations, robust standard errors in parentheses.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

TABLE 3

OLS relationships between pesticide exposure and ln(wages), by pay basis and legal status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	**All**	**All**	**Piece rate**	**Piece rate**	**Hourly**	**Hourly**	**Undocumented**	**Undocumented**	**Documented**	**Documen**
Pesticides	0.0563 ***	0.0703 ***	0.100	0.0870	0.0590 ***	0.0650 ***	0.0319 ***	0.0482 ***	0.0656 ***	0.0763 **
	(0.00746)	(0.00728)	(0.109)	(0.102)	(0.00690)	(0.00642)	(0.0101)	(0.0113)	(0.0100)	(0.00930
Female	0.0751 ***	0.0715 ***	0.119 **	0.124 ***	0.0555 ***	0.0546 ***	0.0687 ***	0.0663 ***	0.0767 ***	0.0712 **
	(0.00718)	(0.00757)	(0.0517)	(0.0354)	(0.00505)	(0.00486)	(0.0107)	(0.0104)	(0.00884)	(0.00867
Age (years)	7.65e–05	5.35e–05	0.00461 ***	0.00428 ***	0.000586 ***	0.000464 **	0.000210	0.000148	0.000183	3.80e–05
	(0.000256)	(0.000251)	(0.00153)	(0.00137)	(0.000225)	(0.000206)	(0.000373)	(0.000362)	(0.000354)	(0.00034
Education (years)	0.0101 ***	0.00917 ***	0.0217 **	0.0168 **	0.00782 ***	0.00607 ***	0.00691 ***	0.00623 **	0.0142 ***	0.0131 **
	(0.00133)	(0.00142)	(0.00940)	(0.00669)	(0.000672)	(0.000625)	(0.00211)	(0.00243)	(0.00141)	(0.00131
Farm experience (years)	0.00213 ***	0.00177 ***	0.00624 **	0.00635 **	0.000731 **	0.000606 **	0.00374 ***	0.00209 *	0.00199 ***	0.00215 *
	(0.000403)	(0.000397)	(0.00271)	(0.00260)	(0.000334)	(0.000295)	(0.000907)	(0.00115)	(0.000477)	(0.00043
Tenure (years)	0.00644 ***	0.00657 ***	0.00804 **	0.00980 ***	0.00674 ***	0.00640 ***	0.00769 ***	0.00858 ***	0.00619 ***	0.00586 *
	(0.000502)	(0.000477)	(0.00332)	(0.00317)	(0.000457)	(0.000427)	(0.00101)	(0.000981)	(0.000566)	(0.00052
Has spouse in the United	0.0502 ***	0.0475 ***	0.0289	0.0175	0.0493 ***	0.0438 ***	0.0226 **	0.0170 *	0.0769 ***	0.0719 **
States	(0.00642)	(0.00616)	(0.0389)	(0.0343)	(0.00509)	(0.00469)	(0.00935)	(0.00879)	(0.00872)	(0.00808
Children (number)	0.0102 ***	0.00954 ***	0.00594	0.0113	0.00889 ***	0.00822 ***	0.00683	0.00432	0.0120 ***	0.0138 **
	(0.00249)	(0.00228)	(0.0171)	(0.0122)	(0.00189)	(0.00176)	(0.00462)	(0.00401)	(0.00309)	(0.00283
Naturalized citizen	0.0546 ***	0.0514 ***	0.0589	0.0199	0.0607 ***	0.0531 ***			0.0683 ***	0.0544 **
	(0.0156)	(0.0150)	(0.157)	(0.153)	(0.0130)	(0.0125)			(0.0213)	(0.0198)
Green Card or other author	0.00480	0.00661	0.120	0.0301	0.00499	0.00881			0.0224	0.0181
	(0.0160)	(0.0153)	(0.0998)	(0.0975)	(0.0116)	(0.0108)			(0.0244)	(0.0224)
Undocumented	0.00325	0.0117	0.00164	0.0349	0.00680	0.000392				
	(0.0151)	(0.0148)	(0.0966)	(0.0979)	(0.0119)	(0.0112)				
Speaks English	0.0242 ***	0.0209 ***	0.0755	0.0792	0.0405 ***	0.0336 ***	0.0255 **	0.0248 **	0.0200 *	0.0165
	(0.00804)	(0.00757)	(0.0553)	(0.0484)	(0.00620)	(0.00574)	(0.0117)	(0.0112)	(0.0116)	(0.0109)
From Mexico	0.0108	0.0287 ***	0.00530	0.0362	0.0196 **	0.0335 ***	0.00988	0.0269 **	0.0126	0.0178
	(0.0107)	(0.0103)	(0.0609)	(0.0628)	(0.00830)	(0.00788)	(0.0122)	(0.0117)	(0.0212)	(0.0198)
Constant	2.119 ***	2.244 ***	2.261 ***	2.879 ***	2.085 ***	2.240 ***	2.137 ***	2.244 ***	2.066 ***	2.192 ***
	(0.0206)	(0.0224)	(0.128)	(0.262)	(0.0142)	(0.0166)	(0.0222)	(0.0290)	(0.0234)	(0.0269)
Crop, task, year, and region fixed effects?	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	32,242	32,242	2725	2725	27,369	27,369	16,191	16,191	16,050	16,050
$R2$	0.163	0.229	0.094	0.216	0.226	0.341	0.089	0.180	0.165	0.238

Source: NAWS and author calculations, robust standard errors in parentheses.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

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TABLE 4.

Impacts on ln(wages) of pesticide exposure and legal status interactions

Variables	All	All	Piece rate	Piece rate	Hourly	Hourly
Pesticides	0.0975***	0.111***	0.163**	0.0692	0.0757***	0.0869***
	(0.0146)	(0.0135)	(0.0814)	(0.105)	(0.0150)	(0.0138)
Pesticide*Naturalized citizen	0.0407	0.0431	1.324***	1.314***	0.0281	0.0261
	(0.0333)	(0.0319)	(0.302)	(0.315)	(0.0251)	(0.0225)
Pesticide*Green Card/ other author	0.0767***	0.0725***	0.0415	0.124	0.0253	0.0304*
	(0.0190)	(0.0176)	(0.104)	(0.155)	(0.0185)	(0.0166)
Pesticide*Undocumented	0.0650***	0.0660***	0.215	0.120	0.0271*	0.0388**
	(0.0176)	(0.0172)	(0.151)	(0.159)	(0.0164)	(0.0154)
Female	0.0755***	0.0723***	0.123**	0.126***	0.0557***	0.0550***
	(0.00718)	(0.00755)	(0.0519)	(0.0356)	(0.00504)	(0.00484)
Age (years)	3.77e-05	8.20e-05	0.00454***	0.00412***	0.000602***	0.000484**
	(0.000255)	(0.000249)	(0.00151)	(0.00135)	(0.000225)	(0.000205)
Education (years)	0.00999***	0.00907***	0.0215**	0.0167**	0.00779***	0.00603***
	(0.00133)	(0.00142)	(0.00940)	(0.00673)	(0.000674)	(0.000627)
Farm experience (years)	0.00204***	0.00170***	0.00574**	0.00584**	0.000700**	0.000576*
	(0.000401)	(0.000396)	(0.00267)	(0.00256)	(0.000334)	(0.000295)
Tenure (years)	0.00649***	0.00660***	0.00986***	0.0113***	0.00677***	0.00642***
	(0.000498)	(0.000474)	(0.00294)	(0.00285)	(0.000457)	(0.000427)
Has spouse in the United States	0.0499***	0.0471***	0.0224	0.00990	0.0494***	0.0438***
	(0.00641)	(0.00616)	(0.0385)	(0.0339)	(0.00507)	(0.00468)
Children (number)	0.0106***	0.00993***	0.00605	0.0116	0.00904***	0.00840***
	(0.00248)	(0.00227)	(0.0171)	(0.0123)	(0.00188)	(0.00175)
Naturalized citizen	0.0243	0.0186	1.129***	1.203***	0.0385*	0.0326
	(0.0321)	(0.0308)	(0.301)	(0.309)	(0.0231)	(0.0205)
Green Card or other author	0.0558**	0.0511**	0.0744	0.0934	0.0152	0.0153
	(0.0222)	(0.0210)	(0.115)	(0.156)	(0.0194)	(0.0174)
Undocumented	0.0555**	0.0655***	0.205	0.0781	0.0154	0.0324*
	(0.0216)	(0.0218)	(0.168)	(0.165)	(0.0184)	(0.0174)
Speaks English	0.0259***	0.0226***	0.0829	0.0849*	0.0412***	0.0345***
	(0.00807)	(0.00759)	(0.0555)	(0.0485)	(0.00619)	(0.00574)
From Mexico	0.0103	0.0282***	0.00672	0.0370	0.0192**	0.0334***
	(0.0107)	(0.0103)	(0.0610)	(0.0631)	(0.00832)	(0.00789)
Constant	2.107***	2.234***	2.272***	2.881***	2.081***	2.235***
	(0.0204)	(0.0222)	(0.128)	(0.264)	(0.0143)	(0.0167)
Crop, task, year, and region fixed effects?	No	Yes	No	Yes	No	Yes
R^2	0.166	0.231	0.111	0.230	0.227	0.342

Source: NAWS and author calculations, robust standard errors in parentheses.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.