Salaries or Piece Rates: The Importance of Endogenous Matching between Harvest Workers and Crops

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Abstract

The objective of this paper is to determine whether the choice of payment schemes (hourly versus piece rates) can be systematically explained by the risk aversion of the workers that select them. Most of the previous empirical literature tested the inverse relationship between risk and incentives based on the prediction of the single principal-agent pair model and found mixed results. We derive the equilibrium endogenous matching relationship between agents' risk aversion and the power of contract incentives in a market with many heterogenous principals and agents. Depending on whether the underlying matching between agents' risk aversion and the riskiness of the jobs is of positive assortative or negative assortative type, the relationship is either negative or undetermined. Using confidential data from the National Agricultural Workers Survey (NAWS), we found a weak empirical evidence of matching between agricultural workers risk aversion and crops they harvest. When controlling for endogenous matching our results show that high risk-averse workers choose hourly rates and low risk-averse workers choose piece rates.

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1 Introduction

Much of the empirical and theoretical work on the provision of incentives in firms concerns the choice between the pay-for-performance (piece rates) and salaries (time rates) in labor contracts. Two theories, with sometimes empirically hard to distinguish predictions, dominate the literature. The first is the *ability to perform* explanation of the performance pay which underlies Lazear's (2000) famous paper on Safelite Glass Corp. Because a piece rate allows the more able employees to work harder and earn more, whereas the hourly wage does not, higher ability workers prefer piece rates. The second explanation is found in the traditional *agency theory* that emphasizes the trade-off between risk sharing and provision of incentives (e.g. Holmstrom and Milgrom, 1987). According to the standard principal-agent model, the shape of an optimal contract should inversely depend on the agent's risk aversion and the riskiness of the project. That means that more risk-averse agents always face lower powered incentive schemes (salaries) and less risk-averse agents face higher powered schemes (piece rates). Similarly, riskier projects are always contracted with less incentives and more insurance and *vice versa*.[1]

These theoretical results have generated a very large empirical literature in areas such as sharecropping, executive compensation, franchising, etc. Predergast (2002) provided an excellent survey of this literature and argued that very few papers, however, have confirmed the negative relationship between pay for performance and observed measures of uncertainty, while the majority of them either discovered a positive or no significant relationship between the two phenomena. As the result, the authors of these studies are either completely dismissive of the agency theory's explanation of the importance of risk and risk aversion for contract choice or they try to modify the agency theory's risk-incentives trade-off to explain what has been empirically observed.[2]

[1]In a multitasking setting, Holmstrom and Milgrom (1991) demonstrate that providing incentives for some tasks could induce a misallocation of effort across tasks, and when this is sufficiently severe, the theory predicts that incentive pay should not be used.

[2]For example, Allen and Lueck (1999) resort to transaction costs arguments to explain the emergence of various contract forms. Prendergast (2002) tries to account for the effect of uncertainty on incentives through

One surprisingly common characteristic of the vast majority of empirical papers is the fact that they ignore the possibility of endogenous matching between principals and agents. Despite the fact that the data usually comes from a market which consists of heterogenous principals and agents, they test predictions which emerge from an isolated principal-agent pair described above.[3] It is easy to see that if one allows the workers to be different with respect to their risk aversions, and also allows projects (tasks, jobs) to be different with respect to their riskiness, then perhaps from the social welfare point of view it would be best if agents with low risk aversion work on very risky projects and workers with high risk-aversion work on less risky projects. If this endogenous equilibrium materializes in the economy and either the agents' risk-aversions or the riskiness of the projects are unobservable, one could end up with a spuriously positive relationship between risk aversion and the power of incentives. This could be the case if, for example, workers with high risk aversion matched with low risk projects and ended up signing high incentive contracts, resulting in a positive slope coefficient in a regression of the power of incentives on risk aversion.

This problem has been first recognized by Ackerberg and Botticini (2002) who illustrated that in the presence of endogenous matching the degree of risk-aversion is correlated with the riskiness of the project and since risk-aversion cannot be measured accurately, its error is correlated with the principal's characteristics causing the endogeneity bias. They argue that potential solutions to this problem involve the estimation of a *matching equation* that describes how principals and agents are matched with each other. They suggest the use of instruments that affect the matching equation but do not affect the contractual choice. They apply their technique to historical data on contracts between landlords and tenants in early

the allocation of responsibility to employees. Fukunaga and Huffman (2009) trying to explain landlord-tenant choices of share versus cash-rent contracts focus on the contribution of explanatory variables that represent transaction costs, risk-sharing incentives, or both.

[3]A different strain of literature, inspired by the competitive insurance model of Rothschild and Stiglitz (1976), has recently emerged, see for example Balmaceda (2009). In these competitive screeing/sorting models, the appearance of pay for performance schemes has nothing to do with incentives to exert effort, but are rather the consequence of solving adverse selection problems.

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The earliest contribution to the endogenous matching literature is Becker's (1973) marriage market paper. More recent contributions are, for example, Legros and Newman (2002), Besley and Ghatak (2005), Courty and Marschke (2008) and Serfes (2005; 2008). The endogenous matching model presented in the first part of our paper is a direct extension of Serfes (2005) who derived the equilibrium relationship between the principal's risk and the power of incentives whereas we derive the relationship between the agents' risk aversion and the power of contract incentives. The direction of this relationship fundamentally depends on whether the underlying matching between agents and projects is of positive assortative (PAM) or negative assortative (NAM) type. In our context PAM would be the situation when low risk-averse workers match with crops that exhibit low risk in harvesting and workers with high risk aversion match with crops that exhibit high risk in harvesting. NAM is characterized by the exactly opposite situation. If matching is positively assortative, then the model generates the unique prediction of a negative relationship between risk aversion and incentives. However, if matching is negatively assortative the theory gives no definitive prediction and the relationship between agents' risk aversion and the power of incentives remains an empirical question.

Using the confidential version of the National Agricultural Workers Survey (NAWS), we found some evidence of statistically significant matching between agricultural workers' risk aversion and crops they harvest. However, because the nature of the data does not allow us to estimate the slope of the matching equation (type of matching), the relationship between workers' risk aversion and the power of incentives remains an empirical question. When controlling for endogenous matching between workers and crops by using county and crop fixed effects, we empirically show that low risk-averse (wealthier) workers choose compensation schemes with stronger incentives (piece rates) and vice-versa.

2 The Model

Consider an isolated principal-agent pair where a risk-neutral principal contracts a risk-averse agent to perform a certain risky task. The production function for this task is given by $y_{p,a} = e_a + \epsilon_p$ where e_a is the agent's unobservable effort and $\epsilon_p \sim N(0, \sigma_p^2)$ is the *i.i.d.* productivity shock. The agent's cost of effort is given by $C_a = \frac{c}{2}e_a^2$ and she is assumed to have constant absolute risk-aversion (CARA) preferences with the utility function given by $V = 1 - exp[-\lambda_a(w_{p,a} - \frac{c}{2}e_a^2)]$, where w represents the compensation. The principal's profit (utility) function is simply $\pi = y_{p,a} - w(p, a)$. Both players have zero reservation utilities.

The above set-up presents a standard hidden action moral hazard problem where the optimal compensation scheme is linear in output (Holmstrom and Milgrom, 1987) such that $w_{p,a} = \alpha_{p,a} + \beta_{p,a}y_{p,a}$ where α is the fixed salary and the optimal piece rate (that maximizes the principal's expected profit subject to the agent's incentives compatibility and individual rationality constraints) is given by:

$$\beta_{p,a} = \frac{1}{1 + c\lambda_a\sigma_p^2}. \tag{1}$$

It clearly follows from (1) that the optimal piece rate is inversely related to the agent's absolute risk aversion parameter as well as the riskiness of the task. In other words, the higher the degree of agent's risk aversion and the riskier the task, the lower the power of incentives. As mentioned in the introduction, these predictions have generated a large empirical literature across many fields and markets (see Prendergast, 2002).

Next, we need to embed this isolated principal-agent pair into a market with many heterogenous principals and many heterogenous agents to study the equilibrium matching patterns among them. In particular, let's consider a market where principals (employers) are uniquely identified by the riskiness (variance) of their tasks (projects) and are uniformly distributed on the interval $[\sigma_L^2, \sigma_H^2]$ and agents (workers) are uniquely identified by the degree of their absolute risk aversion and are uniformly distributed on the interval $[\lambda_L, \lambda_H]$. We assume that one principal has to match with exactly one agent (and vice versa) to produce output.

Following Serfes (2005), we focus on monotone (assortative) matching.[4] We start by stating three sets of definitions. First, for ease of exposition, we define *good* types by low variance of tasks (in case of principals) and low degree of risk aversion (in case of agents) and *bad* types by high variance of projects (principals) and high degree of risk aversion (agents). Next we define positively assortative matching (PAM) when good type principals match with good type agents and bad type principals match with bad type agents (the matching curve has a positive slope). We define negatively assortative matching (NAM) when good type principals match with bad type agents or the opposite (the matching curve has a negative slope). Finally, we say that the total surplus function is supermodular if the traits of the principals and the agents (variance of tasks and degree of risk aversion) are complements. Alternatively, we say that the surplus function is submodular if the traits are substitutes.[5]

The literature on assortative matching typically assumes that the surplus function is either supermodular or submodular. In this case, we cannot *a priori* make such an assumption because in the principal-agent case the surplus function is not part of the data of the problem but rather the outcome of the principal-agent interaction.[6] Therefore, one needs to investigate conditions under which this function is is either supermodular or submodular or both. Given that the only coalitions that matter are of size two, assuming transferable utilities and no externalities across coalitions, any reasonable solution concept should maximize aggregate surplus (see also Legros and Newman (2002)). Utilizing the fact that $\epsilon_p \sim N(0, \sigma_p^2)$, the agent's CARA utility function can be expressed in the mean-variance form, upon which the solution to the optimal effort can be obtained as $e_a^* = \beta_{p,a}/c$ and the expected surplus function $\Pi_{p,a} = E(\pi + V)$ becomes $\Pi_{p,a} = \frac{\beta_{p,a}}{c} - \frac{\beta_{p,a}^2}{2c} + \frac{\lambda_a}{2}\beta_{p,a}^2\sigma_p^2$. Now using the formula for

[4]Serfes (2005) analyzed the relationship between the riskiness of the tasks and the power of incentives under equilibrium matching between heterogenous principals and agents, whereas we analyze the relationship between the agents' risk-aversion and the power of incentives. For a more general approach based on Shapley and Shubik's (1972) assignment game, see Serfes (2008).

[5]For formal definitions of supermodularity and submodularity see Milgrom and Roberts (1990).

[6]Intuitively though, with agents' risk aversion and riskiness of the tasks as traits, one would expect that the traits are substitutes and the profit function is submodular.

the optimal piece rate (1), the expected surplus function becomes:

$$\Pi_{p,a} = \frac{1}{2c(1 + c\lambda_a \sigma_p^2)}. \tag{2}$$

The sufficient conditions for assortative matching are obtained by looking at the cross-partial derivatives of the expected surplus function (2) to determine whether the function is supermodular or submodular. The results show (see Appendix A.1. for the formal proof) that if the product of the low ends of the supports of the principals' and agents' distributions is relatively high, i.e., in the market where the degrees of risk aversion and/or the riskiness of the projects are high, agents with high degrees of risk aversion are matched with principals who own high risk projects and vice versa (PAM). Conversely, if the product of the high ends of the supports of the types distributions is relatively low, i.e., in markets where the degrees of risk aversion are low and/or the riskiness of the projects are low, agents with low degrees of risk aversion should efficiently match with high risk principals and vise versa (NAM).

Now, let's turn to the main result of this section: the equilibrium relationship between risk aversion and incentives under endogenous matching among heterogenous principals and agents. First, we assume PAM. Using a *measure consistency* condition which says that the mass of principals has to be equal to that of agents since each principal is matched with exactly one agent and vice versa (see Legros and Newman (2002)), it must be the case that

$$\int_{\sigma_L^2}^{\sigma^2} \frac{dx}{\sigma_H^2 - \sigma_L^2} = \int_{\lambda_L}^{\lambda} \frac{dy}{\lambda_H - \lambda_L}. \tag{3}$$

After some straightforward manipulation, expression (3) yields the equilibrium relationship between the riskiness of the principal's project (asset) and the degree of agent's risk aversion: $\sigma^2 = \frac{\lambda_H \sigma_L^2 - \lambda_L \sigma_H^2}{\lambda_H - \lambda_L} + \lambda \left(\frac{\sigma_H^2 - \sigma_L^2}{\lambda_H - \lambda_L} \right)$, which after inserting it into (1) yields:

$$\beta(\lambda) = \frac{\lambda_H - \lambda_L}{(\lambda_H - \lambda_L) + c\lambda(\lambda_H \sigma_L^2 - \lambda_L \sigma_H^2) + c\lambda^2(\sigma_H^2 - \sigma_L^2)}. \tag{4}$$

The differentiation of (4) with respect to λ gives:

$$\frac{d\beta}{d\lambda} = \frac{-(\lambda_H - \lambda_L)\left[c(\lambda_H \sigma_L^2 - \lambda_L \sigma_H^2) + 2c\lambda(\sigma_H^2 - \sigma_L^2)\right]}{\left[(\lambda_H - \lambda_L) + c\lambda(\lambda_H \sigma_L^2 - \lambda_L \sigma_H^2) + c\lambda^2(\sigma_H^2 - \sigma_L^2)\right]^2}. \tag{5}$$

By evaluating the sign of the derivative (5) one can determine the effect of the change in agent's risk aversion on the power of incentives in the principal-agent contracts.

Proposition 1: In case of a PAM, the resulting equilibrium relationship between agents' risk aversion and the power of the contract incentives is always negative. Agents with high degree of risk aversion will sort themselves into low powered incentives contracts, and vice versa.

Proof: Appendix A.2.

Combining the results of Proposition 1 with the corresponding equilibrium matching we obtain a rather interesting result. Since the equilibrium matching is positively assortative, agents with high degrees of risk aversion are matched with principals who own high risk projects but they pick low powered incentives schemes. Conversely, agents with low degrees of risk aversion are matched with principals owning low risk projects but they pick high powered incentives schemes. This result is interesting because it gives the same prediction about the relationship between risk aversion and the power of incentives as in the case of a single principal-agent pair (1), but which is based on a counter-intuitive risk matching result where the traits (agents' risk aversion and the riskiness of the tasks) are complements.

Now, let's look at the negatively assortative matching. As it turns out, in case of a NAM, the resulting equilibrium relationship between agents' risk aversion and the power of the contract incentives can be positive, negative, or U-shaped (see Proposition 2 and its proof in Appendix A.3.). Based on these results we see that in cases where traits are substitutes (as economists intuitively believe), the theoretical model gives no definitive empirical prediction about the relationship between risk aversion and the power of incentives. The relationship between the agent's risk aversion and the type of payment he would choose can be either positive or negative. This result provides a very good explanation why few papers confirmed the negative relationship between pay for performance and observed measures of uncertainty, while the majority of them either discovered a positive or no significant relationship between the two phenomena (Prendergast, 2002).

3 Data

To estimate the relationship between the agents' risk aversion and the power of contract incentives, we use confidential individual-level data on harvest farm workers from the National Agricultural Workers Survey (NAWS) from 2000 to 2007. The difference between the confidential data and the public release version of the NAWS is in the details provided for each individual worker in terms of the location of their employer (down to the county level in the confidential data, but only down to the 6 aggregate regions (East, Southeast, Midwest, Southwest, Northwest, California) in the public release version), and the crops which they harvest (down to the actual crop (e.g. oranges) in the confidential data, but only down to 5 crop aggregates (Field Crops, Fruits and Nuts, Horticulture, Vegetables, and Miscellaneous) in the public release data). The NAWS is the only nationally representative survey of demographic and employment characteristics of hired crop workers. To reflect the seasonality of agricultural production and employment, the crop workers are surveyed in three cycles each year. The information is obtained directly from farm workers through face-to-face interviews.

We use data on undocumented harvest farm workers, i.e. crop workers without permanent U.S. residence. There are two reasons for this choice. First, not surprisingly, most harvest farm workers in the U.S. are undocumented – about 70 percent of all harvesters during the 2000-2007 period in the NAWS are undocumented. Second, the distribution of risk aversion across U.S. citizens and permanent residents, who are legally allowed to work in the U.S., is likely quite different from the distribution of risk aversion across undocumented workers. While the baseline results shown here use only undocumented workers, similar results obtain using both undocumented workers and legal permanent residents.

Table 1 presents the summary statistics of all undocumented harvest crop workers surveyed in the NAWS between 2000 and 2007. The data shows that 41 percent of workers are paid by the piece (piece rate) as opposed to by the hour (hourly rate), and that their average hourly wage is $7.94 (constant 2006 U.S. dollars).[7] Only 11 percent of all workers are female.

[7]Some workers are also paid by combination of piece rate and hourly rate (5 percent of the total) and about 1 percent of workers are on non-hourly salaries. Both categories are excluded from the analysis currently

About half of all harvesters are married, but only 17 percent have children in the family. At an average age of 28.76 years, these farms workers are fairly young, and while undocumented, they have spent an average of 5.94 years in the U.S. Given their farm work experience in the U.S. of 5.52 years, their predominant form of employment in this country is farm work – only 9 percent were employed outside the agricultural sector. This may not be surprising as they have fairly low levels of education with an average of 6.06 years of schooling. Many of them do not speak English well. Their average proficiency in spoken English on a scale of 1 (worst) to 4 (best) is only 1.38. Most workers in this population (78 percent) are full-time employees with an average of 41.04 hours per week, and about one third are employed by a farm labor contractor as opposed to directly by the farm.

While the NAWS does not record the value of personal assets, it offers a very detailed classification of all assets an agricultural worker can possess. In particular, existence of 4 different types of assets in each the home country and the U.S. is recorded. Crop workers indicate if they own land, a business, a house, or other assets both in their home country, which is Mexico for about 96 percent of the sample, and in the U.S.[8] In our analysis, we use these 8 indicator variables as empirical proxies of harvest workers' wealth. We do not combine all 8 variables into one wealth indicator (or two – one for their home country and one for the U.S.) because the assets in each of these 4 categories across the two countries are likely of quite different values. For example, the value of a house in Mexico may be larger than the value of a plot of land in Mexico, and smaller than the value of a house in the U.S. The summary statistics in Table 1 reveal that undocumented harvest workers own few assets in the U.S. Only 0.2 percent of this population own land in the U.S., and only 0.1 percent own a business or other assets. Also, a small fraction of workers (1.8 percent) own a house

reported in the paper. However, we estimated the contract choice equation (piece rate equation, see next section) recoding the combination workers as piece-rate and the salaried as hourly rate, and the results (available from authors upon request) are almost identical to those reported here.

[8]Among other assets in the U.S., respondents specified "bicycle/motorcycle", "building", "cattle", and "part of a farm/hunting camp". Other assets in the respondent's home country include "cattle", "horses/donkey", and "apartment".

in the U.S. When it comes to assets in their home country, a much larger fraction of the harvesters own land (11.1 percent) or a house (46.9 percent). A smaller number of workers own a business (0.02 percent) or other assets (0.02 percent) in their home country.

Table 2 presents the sample correlations across the 8 different wealth indicators and the type of compensation. The first column of Table 2 implies that wealth is not really correlated with piece rate pay – the coefficients are of rather small magnitude, with some being positive, and some being negative. Not surprisingly, the highest (positive) correlations documented are between ownership of a house and land either in the U.S. or in the worker's home country.

The summary statistics reported in Table 1 also reveal that half of all harvesters live within 9 miles of their place of employment, and nearly 90 percent live within 25 miles. For the vast majority of them (96 percent), Mexico is their home country. More than half of all workers (54 percent) harvest various fruits and nuts, and 33 percent pick vegetables. Not surprisingly, a large fraction of all harvest workers are employed in California (41 percent); the second largest region in terms of employment is the Southeast (22 percent). As mentioned earlier, the empirical analysis in this study will use confidential data that provides much more precise information on the crops that workers harvest and the county of their employment.

4 Econometric Specification

In order to establish the correspondence between the presented theory and the available data, we need to explain how are the principals' and agents' characteristics (traits) going to be defined and measured.

First, it is important to realize that the riskiness of the principals' assets (projects) in this context is the riskiness associated with harvesting a particular crop and not the riskiness of producing (growing) that crop (although there could be some commonalities between the two). It is the first that matters and not the second, because here we are dealing with the harvesting contracts where risk is different than, for example, in sharecropping contracts. To fix ideas, imagine two crops being harvested with two types of equipment, one prone to frequent malfunctioning and stalling and the other very primitive but always functioning flawlessly. Some harvesters may prefer the second job, albeit physically more strenuous, because it could be perceived as less risky. Another situation may be weather related. Imagine that some harvesting is easily done when it rains whereas some other harvesting in the rain is strongly discouraged. Then, if it starts raining during harvest, the piece rate harvesters are wasting their time because they are not earning any income, whereas the hourly rate workers do not mind rain because they are getting paid regardless of whether they are active or idle. Finally, the riskiness of growing a crop, as typically represented by its yield, can also play a role in harvesting. When the yields are low, the harvesters may use more time to pick a certain quantity compared to harvesting when yields are high. The hourly paid work force would be indifferent between the two yield scenarios whereas the piece rate crew would always prefer to harvest a bumper crop.

Second, the fact that agents' (farm workers') risk aversion or risk tolerance is not directly observable presents a challenge for empirical work. In our approach we rely primarily on the most recent work by Guiso and Paiella (2008) who used survey data on households' willingness to pay for a hypothetical risky security to recover a measure of the Arrow-Pratt index of absolute risk aversion of the consumer lifetime utility. Their findings show that risk aversion (risk tolerance) is a decreasing (increasing) function of consumers' resources, thus rejecting the constant absolute risk aversion (CARA) preferences. They also estimated the elasticity of absolute risk tolerance to consumers' resources to be below unity as implied by the constant relative risk aversion preferences (CRRA) which then suggests that risk tolerance is a concave function of wealth.[9] In particular, we use a vector of workers resource endowments as a proxy for risk aversion. The measure is coded as 8 dummy variables that indicate if harvest worker i owns land, a house, a business, or other assets in the U.S. or their home country. In line with all existing literature, we postulate that wealthier individuals are less risk averse.

[9]Wealth was used as a proxy for risk aversion in many other studies, e.g. Laffont and Matoussi (1995) and Ackerberg and Botticini (2002).

4.1 Matching Equation

Based on the previously presented theoretical model, an obvious first step in the empirical analysis would be to determine whether the ongoing matching process is of positive assortative (PAM) or negative assortative (NAM) type. If it turns out that the underlying matching process is PAM, then based on Proposition 1, we have a clean theoretical prediction that highly risk-averse workers should end up choosing hourly rates whereas low risk-averse agents would choose piece-rates. Unfortunately, since there is really no meaningful way to ascribe or compute the risk associated with harvesting each particular crop, it became impossible to estimate the slope of the matching equation by simply regressing the risk associated with the principal's task on the agent's measure of risk aversion.

However, utilizing the detailed information on the type of crop each harvester chooses, we can still test if any kind of matching between workers and tasks is going on. This is accomplished by estimating a multinomial logit model, where the left-hand-side variable is the probability that harvest worker i chooses crop k, P_{ik}, and the right-hand-side variable is the measure of this worker's risk aversion. Workers can potentially select from a set of more than 50 available crops.[10] In addition to the worker's wealth, W_{ijkt}, which is used as a proxy for risk aversion, the regressors include a vector of personal characteristics, X_{ijkt}, and the set of year dummies, $Year_t$:

$$P_{ik} = \frac{e^{(X_{ijkt}\alpha_{1k} + W_{ijkt}\alpha_{2k} + Year_t)}}{1 + \sum_{k=2}^{K} e^{(X_{ijkt}\alpha_{1k} + W_{ijkt}\alpha_{2k} + Year_t)}}. \tag{6}$$

The vector of personal characteristics, X_{ijkt}, for worker i, harvesting crop k in county j in year t ($t = 2000, 2001, ..., 2007$) includes controls for schooling, English proficiency, gender, marital status, children, age, time spent in the U.S., a linear and a square term in U.S. farm work experience, and indicators for non-farm employment, full-time status, and employment by a farm labor contractor. For identification, one of the crop choices ($k = 1$) is treated as

[10]There are 92 potential crop choices in the data. We use more aggregated 45 crop choices when estimating the matching equation for technical and computational reasons. In the contract choice model presented later, we use all of the original disaggregated 92 crop choices.

the base category (the correspondent coefficients are constraint to equal 0). In our case the base crop is oranges. At the very basic level, this model will provide evidence of matching between harvest workers (based on their risk aversion) and the crops they harvest within any given year of employment.

4.2 Contract Choice Equation

Next, we estimate the following empirical contract choice equation that relates the outcome of interest, i.e., the incidence of piece rate vs. hourly rate, to individuals' characteristics and risk aversion:

$$R_{ijkt} = \beta_0 + X_{ijkt}\beta_1 + W_{ijkt}\beta_2 + \text{Crop}_k + \text{County}_j + \text{Year}_t + \epsilon_{ijkt} \tag{7}$$

The dependant variable R_{ijkt} is an indicator equal to one if individual i, employed in county j, harvesting crop k in year t is paid by a piece rate, and zero if he is paid by an hourly rate. The vector of personal characteristics X_{ijkt} includes the same controls as it did in the matching equation (6) and risk aversion is proxied by wealth, W_{ijkt}. Since wealthier workers are less risk averse, they should be more likely to choose piece rates as opposed to hourly pay. Therefore, we expect positive coefficients on all of the 8 wealth indicator variables.

We estimate a linear probability model instead of a probit or a logit model because employing maximum likelihood estimator with a large number of fixed effects (indicator variables) is computationally challenging.[11] Additionally, the mean of the left-hand side variable R_{ijkt} is about 0.4, far away from the end points of the $[0, 1]$ interval, implying that the linear probability model will deliver results that are very close to those of the probit or logit specification.[12]

Note that regression equation (7) explicitly controls for the crop the worker harvests and the county of employment, and as such, the estimates are within-crop and within-county. It

[11] In our preferred specification, we include nearly 200 county and crop fixed effects.

[12] Also, the estimated coefficients of the linear probability model are readily interpretable, unlike those of the probit and logit specifications.

is important to include both crop and county fixed effects because of the possible matching between harvest workers and crops previously discussed. Additionally, the harvesting technology for certain crops are much more likely to require hourly pay vs. piece rate pay – for example, table grapes require much more careful harvesting (in order to avoid squishing the grapes) than do wine grapes. As a result harvesting table grapes is likely to pay predominantly by the hour, while harvesting wine grapes by the piece. Consistent with differences in harvesting technology, Table 3 provides evidence that harvesting table grapes has an incidence of piece rates of 0.15, while the incidence of piece rates for wine grapes is 0.65. Controlling for county of employment is important because the same crop produced in two different regions could be different and hence require different harvesting practices. Also, county fixed effects control for workers' alternative employment opportunities that determine their reservation utilities, which likely vary with geographical location.

5 Results and Discussion

Following the structure of the exposition so far, we first discuss the empirical results from the matching equation and then the findings from the contract choice model.

5.1 Matching Results

As mentioned before, in this section the base crop category is oranges and all estimates are relative to those of oranges. Because there is a very large number of estimates – 44 different set of estimates for the 45 different crops (crop categories) – we only present one of the crop categories – strawberries. The estimation results from equation (6) are presented in the first column of Table 4. The second column presents the results where the county fixed effects have been added.

As seen from the first column results, a number of the estimated coefficients on the personal characteristics are statistically significant. They suggest that women, full-time workers, and those who have children in the family are more likely to harvest strawberries than oranges. On the other hand, older workers and those employed by a farm labor contractor (and not directly by the farmer) are less likely to harvest strawberries. More importantly, we also see that some of the risk aversion (wealth) indicators are statistically significant at the 5 or 10 percent level. These estimates provide some evidence of matching based on the project riskiness (harvesting of a particular crop) and the agent's risk aversion. In particular, the results imply that wealthier, and hence less risk averse harvesters, are less likely to pick strawberries (relative to oranges), whose growers are also significantly less likely to pay by the piece relative to orange growers (see Table 3), making strawberry picking a less risky alternative than picking oranges.

Adding county fixed effects to the matching equation (6) fundamentally changes the previous results. As seen from column (2) of Table 4, none of the within-county estimated coefficients on the personal characteristics are statistically significant at the 5 percent level. The two that come closest are the coefficients on the female (vs. male) indicator and the indicator for employment by a farm labor contractor (and not directly by the farmer). However, both of these coefficients are about 3 to 5 times smaller in magnitude than their counterparts in column (1). More importantly, none of estimated coefficients on the 8 wealth indicators are statistically significant, and compared to their counterparts in column (1), these estimates are much smaller in magnitude and are all very close to zero.

Similar results hold for the other 43 crops relative to oranges.[13] Without county dummies, some of the risk (wealth) indicators are statistically significant at the 5 or 10 percent level. For some crops (relative to oranges), wealth has a positive effect, while for others, it has a negative effect. In general, the coefficients on most of the wealth indicators are negative for the majority of the remaining crops. Once the county fixed effects are added to the matching equation the significance completely disappears. All of these results imply that any matching that occurs actually takes place at the national level by harvest workers moving to counties where there are crops that they would prefer to harvest. Once the county of employment is determined, matching patterns disappear, i.e. within a county, there is no evidence of

[13]The estimation results are available from authors upon request.

matching between harvest workers and crops based on the crop's risk in harvesting and the worker's risk aversion.

The absence of strong empirical support for the claim that principals and agents are endogenously matched based on the chosen traits is somewhat surprising but not impossible to imagine. An obvious explanation of the obtained result is that matching in this particular context is not important. Harvest workers randomly pick crops that they harvest because the difference in riskiness across crops is not significant enough for workers to pay close attention to. In cases with no systematic matching between workers and tasks, we are back on the territory of the single pair principal-agent moral hazard model which predicts the inverse relationship between agents' risk aversion of the power of incentives.[14]

Despite the fact that the matching equation estimates do not inconclusively confirm the presence of endogenous matching between workers and crops and as such are not helpful in narrowing down the predictions of the theoretical model, this step is still useful from the econometrics point of view. Estimating a matching equation such as this is in fact what Ackerberg and Botticini (2002) suggest as a check for endogeneity when regressing the contract choice on the riskiness of the task and the worker's wealth, when wealth is not a perfect proxy for risk aversion. Because conditional on worker's location (county of employment), we find no evidence of matching, the contract choice equation we estimate next, which also controls for county of employment, should not suffer from the endogeneity problem.

5.2 Contract Choice Results

The estimates from the contract choice model (7) are presented in Table 5. We start by estimating the simplest specification which does not include any of the county, crop, and

[14]Another possibility might be that not having detailed crop risk measures is a problem. Using crop indicators directly as the measurements of their riskiness could be hampered by the fact that crop indicators may include attributes (other than risk in harvesting) that workers prefer or dislike that are entirely unrelated to harvesting risk and hence entirely unrelated to agents' risk aversion. We don't have enough information to substantiate or dismiss this assertion.

year fixed effects from regression equation (7). The results presented in the first column of Table 5 reveal a number of interesting findings. First, it appears that an extra year of education has a small and negative, though statistically insignificant effect on the likelihood that the harvest worker is paid by the piece rather than by the hour. This result is unexpected given the previous work of Guiso and Paiella (2008) who show, in an experimental setting, that more educated individuals tend to be more risk tolerant, and should therefore be more likely to choose the riskier alternative, i.e. the piece rate.

The estimates also imply that harvesters with higher English proficiency and female workers are less likely to be paid by the piece. The latter is also in contrast with Guiso and Paiella (2008) who find that female headed households are more risk tolerant. While being married increases the probability of piece rate pay slightly, having children and being older has a large, economically and statistically significant negative impact on the likelihood of piece rate pay.[15] In particular, having children decreases this likelihood by 10 percentage points, and 40 year old harvesters have an 8 percent lower probability of being paid by the hour than do 20 year old workers ($= (40 - 20) \times 0.004$). Both time spent in the U.S. as well as U.S. farm work experience have positive effect on the piece rate pay. The impact of U.S. farm work experience is, however, non-linear.

Next, we find that employment by farm labor contractor has a very large and statistically significant positive impact on the probability of piece rate contract. In fact, being employed by a farm labor contractor, and not directly by the farm, increases the likelihood of piece rate pay by 26 percentage points.[16] Given the average incidence of 41 percent (see Table 1), this

[15] The effect of age on the decision whether to work on a piece-rate or time-rate agricultural jobs is also documented in Rubin and Perloff (1993). Based on a sample of harvest workers from Tulare County, California their estimates show that age has a negative impact, and age squared has a positive impact on probability of choosing piece rate harvest work. When we estimated a specification that includes both age and age squared, we found the same pattern but the impact of age squared was small and insignificant, most likely because we were able to additionally control for experience and experience squared, as well as time spent in the U.S.

[16] The relationship between labor contracting and wages of agricultural workers in California has been studied by Vandeman, Sadoulet, and de Janvry (1991), although they did not distinguish between hourly rates and piece rates. They found that wages paid by contractors are lower than wages in direct hiring, net

represents an increase of 63 percent. The effect of farm labor contractor may, of course, be due to the fact that we have not yet properly controlled for the crop the worker harvests. We later show that this is exactly the case, once we properly control for the crop type, the effect of farm labor contractor entirely disappears. Further, we find that full-time employment (40 or more hours per week) is associated with 18 percentage point lower likelihood of piece rate pay. Similar to the case of farm labor contractor employment, we later show that this large negative effect disappears once we control for county of employment and crop type.

The last 8 estimated coefficients pertain to the 8 wealth indicators. As risk tolerance increases with wealth, we expect that wealthier, less risk averse workers, will choose the riskier, piece-rate contracts. The results, however, appear a bit mixed with some large, positive, and statistically significant coefficients, some large negative and statistically significant coefficients, and some small and statistically insignificant estimates. For example, owning a business in the U.S. has a large negative impact on the likelihood of piece rate pay, while owning a business in the worker's home country has a large positive impact. Except for owning a business, generally, the same type of asset (e.g. land) has the same qualitative impact regardless of its location. For instance, ownership of land both in the U.S. and in the worker's home country has a positive effect on piece rate pay. Overall, the results are a bit surprising - one would expect a clearer positive impact of higher wealth (lower risk aversion) on piece rate pay. However, as we already discussed earlier, this first specification does not control for two very important piece rate pay determinants - the county of employment and the crop the worker harvests. In what follows, we progressively add more and more detailed geographic and crop controls, and show that there is a much stronger and consistent relationship between wealth (risk aversion) and contract choice.

In column 2 of Table 5, we add year dummies to account for the fact that aggregate economic fluctuations may change the piece rate incidence over time. Almost none of the estimated coefficients change from their respective counterparts in column 1. In specification 3, we additionally include the 6 aggregate region dummies (East, Southeast, Midwest,

of differences in the distribution of jobs or workers between the two contract types.

Southwest, Northwest, California; see Table 1). These fixed effects control for region of employment; however, being fairly aggregate in nature, they do not change the estimates appreciably. The two most significant changes are in the coefficients on schooling, which is now positive (0.003) as expected, and full-time employment, which is much smaller at -0.11. The effect of farm labor contractors is also estimated to be smaller at 0.20. The fourth specification (column 4) includes crop category dummies (Field Crops, Fruits and Nuts, Horticulture, Vegetables, Miscellaneous) in addition to the year and region fixed effects. There are only minor changes in the estimated coefficients going from column 3 to column 4. Even with year, region, and crop category dummies, the results are not very different from the estimates in column 1, which included none of the aggregate fixed effects. This is likely due to the fact that the publicly available information on region and crop categories in the NAWS is simply too aggregated. Next, we use the detailed information on harvester's county of work and specific crop of employment available in the confidential version of the NAWS.

The specification in column 5 of Table 5 includes year and county of employment fixed effects. We see three important changes in the estimated coefficients. First, the impact of owning a business in the U.S. has turned from negative, as it was in the previous four specifications (columns 1 to 4), to positive, as we would expect it to be. The estimate now implies that harvest workers who own a business in the U.S. are 13 percentage points more likely to be paid by the piece. The second large change is in the coefficient on the other assets in the home country, which has now jumped to 0.24 in column 5 from a mere 0.03 in column 2. The new coefficient suggests that owning other assets in the home country increases the likelihood of piece rate employment by 24 percentage points, or about 59 percent at the mean of 0.41 (see Table 1). The third change that we note is in the coefficient on being female. This result is now consistent with Guiso and Paiella (2008) who find that female headed households are more risk tolerant, and in contrast to all our previous specifications. In column 5, we document that female workers are 2 percentage points more likely to choose the riskier piece rate pay. The rest of the estimated coefficients do not differ very much from their respective counterparts in specification 4. The much higher R^2 (0.41) in column 5 signals that the county fixed effects have indeed accounted for a large portion of the unexplained variation in either column 2 or column 4 where the R^2 was 0.12 and 0.28 respectively.

Further, in column 6, in addition to year and county of employment fixed effects, we include detailed crop fixed effects. The inclusion of the crop fixed effects significantly increased the R^2 to 0.60. Employing this within-county and within-crop estimator delivers even more significant changes in line with theory and intuition. First, note that the effect of education is now positive, fairly large, and statistically significant, just as expected in light of the previous work by Guiso and Paiella (2008) who find that more educated individuals tend to be more risk tolerant, and should therefore be more likely to choose the riskier piece rate pay. The estimated coefficient of 0.005 on schooling suggests that each additional year of education increases the likelihood of piece rate pay by half of a percentage point. Next, consider the coefficient on being married, which is now slightly larger than it was in any of the previous specifications and it is significant at the 10 percent level. Its magnitude implies that married workers are 3 percentage points more likely to choose piece rate pay as opposed to hourly pay, perhaps because the presence of a spouse may reduce the impact of income shocks and as such increase risk tolerance.

Two other coefficients are substantially different in column 6 than they were in any of our previous specifications – the coefficients on farm labor contractor employment and full-time employment. Both of these were previously very important determinants of piece rate pay. For example, in specification 4, where we included both aggregate region and aggregate crop category fixed effects, the impacts of farm labor contractors and full-time employment were 0.18 (with a standard error of 0.04) and -0.09 (with a standard error of 0.04), respectively. In column 6, the effects of both farm labor contractors and full-time employment disappear almost entirely – their estimated effects are 0.02 (with a standard error of 0.03) and -0.04 (with a standard error of 0.02) with neither being statistically significant. As we speculated earlier, this is due to the fact that farm labor contractors and full-time employment are predominant among crops which mostly pay by the piece. Not surprisingly, once we include crop fixed effects, the impacts of farm labor contractors and full-time employment on piece rate pay disappear.

Next, consider the coefficients on the wealth indicators. Similar to specification 5, and in contrast to all other previous models (1-4), the estimated effect of owning a business in the U.S. is positive and statistically significant. The impact of other assets in the home country is also positive and even larger in column 6 than it was in column 5 (0.29 vs. 0.24). Overall, we see that the estimated effects of all different types of assets (wealth), both in the U.S. and in the worker's home country, are positive, just as expected. The only exception is ownership of a house either in the U.S., or in the worker's home country – the estimated coefficients on those assets while small and statistically insignificant are negative. All of the other 6 asset types in the U.S. and the home country are large and positive, with three of them (business in the U.S., other assets in the U.S., and land in home country) also statistically significant at the 5 percent level.

Another interesting point to note is that generally, the estimated impact of wealth on piece rate pay is larger for assets located in the U.S. – for example, having land or a business in the U.S. appears to have a larger positive impact on piece rate pay than does having land or a business in the worker's home country. This may be due to the fact that these assets are likely to have a higher value in the U.S. than in Mexico (the native country for about 96 percent of all harvest workers). Hence, workers owning such assets in the U.S. are most likely wealthier (and hence less risk averse) than workers owning such assets in their home country.

For robustness, we estimate specification 7 (column 7 of Table 5), which in addition to year, county, and crop fixed effects, includes region-specific time trends that are added to capture any difference in pre-existing trends across the six U.S. regions (see Table 1). The estimated effects in column 7 are quite similar to those reported in column 6, further substantiating the conclusion that wealthier (less risk averse) harvest workers pick riskier projects that pay by the piece and not by the hour.

6 Conclusions

There has a been a great deal of empirical studies looking at the determinants of contractual choice in a variety of situations ranging from historical and modern agricultural contracts, to franchising, executive compensation and payroll. The surprising thing about most of this literature is the fact that theoretical hypotheses underlying the empirical work are almost always based on the results from the model of an isolated principal-agent pair. In this paper we focus on the theoretical and empirical implications of endogenous matching of heterogenous principals and agents and argue that the single pair model results do not necessarily extend into the market setting with multiple participants, with potentially important consequences for empirical work.

In summary, we find it quite surprising that the theoretical model of market matching between heterogenous principals and heterogenous agents provides limited guidance for empirical work. First, the question whether the equilibrium matching is PAM or NAM depends on the very difficult to measure quantities: lower and upper bounds on the distributions of the agents' risk aversion and the riskiness of the projects and the cost of agents' effort. The only practical thing to do is to try to empirically estimate the matching equation and see whether it has a positive or negative slope. Even more surprising is the result that a counter-intuitive PAM (where agents' risk aversion and the riskiness of the tasks are complements) leads to the unique prediction which is identical to the result of the single principal-agent pair model. On the other hand, in case of NAM, where, in accordance with economic intuition, high risk-averse agents match with low risk tasks, there is no definitive prediction about the relationship between risk aversion and incentives, which eloquently explains why so many empirical papers looking for the inverse relationship between risk and incentives found so little empirical support for their hypothesis.

Our empirical exploration into the payment mechanisms used in agricultural labor contracts was motivated by the observation that hired labor for harvesting of different crops is paid by piece rates and hourly rates. Some crops exhibit high degree of uniformity with respect to the payment selection but most of them do not. For example, harvesting of olives is exclusively paid by the piece, harvesting of Christmas trees is always paid by hourly rates, whereas harvesting of nearly everything else is sometimes paid by piece rates and sometimes by hourly rates. Our objective is to see whether the choice of payment schemes can be systematically explained by the risk aversion of the workers that select them. To estimate the relationship between the workers' risk aversion and the power of contract incentives, we use confidential individual-level data on harvest farm workers from the National Agricultural Workers Survey (NAWS) from 2000 to 2007.

Our estimation strategy consists of two steps. In the first step the objective was to estimate the matching equation between workers and crops based on their traits. However, since there is really no meaningful way to ascribe the risk associated with harvesting various crops, it was impossible to determine whether the matching is PAM or NAM. Knowing the matching type would narrow the predictions about the theoretically correct relationship between risk aversion and compensation scheme. Instead, we were only able to assess whether the likelihoods of choosing one particular crop over some other crop are influenced by workers' risk aversion as captured by wealth. We detected some evidence of matching between workers and crops but the effect completely disappears when we consider the within-county estimates. Based on this we conclude that if there is any endogenous matching between workers and crops, it is accomplished by workers' geographical movement in search of crops they prefer to harvest. At the county level, the impetus for endogenous matching seems to be entirely exhausted and we are back to the inverse relationship between risk and incentives as predicted by the single principal-agent pair theory.

In the second step we estimate the contract equation relating the contract choice to workers' risk aversion. The central result of this paper is that, controlling for county and crop specificities, i.e. after accounting for endogenous matching between workers and crops, the estimated impact of wealth, both in the U.S. and in the worker's home country, on the probability of choosing a piece rate relative to an hourly rate is positive. This result confirms that the workers' risk aversion and the power of incentives are negatively related. Less risk-averse (wealthier) individuals would choose piece rates whereas more risk-averse individuals would choose hourly rates. These results cast new light into the previously tenuous trade-off between risk and incentives.

Appendix A.1

The cross-partial derivative of (2) is given by:

$$\frac{\partial \Pi_{p,a}}{\partial \lambda_a \partial \sigma_p^2} = \frac{c\lambda_a \sigma_p^2 - 1}{2(1 + c\lambda_a \sigma_p^2)^3}. \tag{8}$$

Since the denominator is always greater than zero, the sign of (8) depends on the sign of the numerator. The derivative is positive if $\lambda_a \sigma_p^2 \geq 1/c$, and negative if $\lambda_a \sigma_p^2 \leq 1/c$. Therefore, if $\lambda_L \sigma_L^2 \geq 1/c$, then (8) is guaranteed to be positive for all λ and σ^2 in the support of the distributions and the surplus function is supermodular and we obtain positively assortative matching (PAM). On the other hand, if $\lambda_H \sigma_H^2 \leq 1/c$, the function is submodular and we obtain negatively assortative matching (NAM).

Appendix A.2

Proof of Proposition 1: Since the denominator of (5) is always positive, the sign depends on the sign of the numerator. The numerator can be rewritten as $c(\lambda_H - \lambda_L)(-\lambda_H \sigma_L^2 + \lambda_L \sigma_H^2 - 2\lambda\sigma_H^2 + 2\lambda\sigma_L^2)$. Since $c(\lambda_H - \lambda_L) > 0$, the sign of the numerator depends only on the sign of the expression in the parentheses, which can be rewritten as: $-\sigma_L^2(\lambda_H - \lambda) + \sigma_H^2(\lambda_L - \lambda) + \lambda(\sigma_L^2 - \sigma_H^2) < 0$, which is obviously negative since all three elements of the sum are negative. **Q.E.D.**

Appendix A.3

In case of negatively assortative matching (NAM), the measure consistency condition is

$$\int_{\sigma_L^2}^{\sigma^2} \frac{dx}{\sigma_H^2 - \sigma_L^2} = \int_{\lambda}^{\lambda_H} \frac{dy}{\lambda_H - \lambda_L}. \tag{9}$$

Going through the same sequence of steps as with PAM we can determine the effect of the change in agent's risk aversion on the power of incentives by evaluating the sign of the following derivative:

$$\frac{d\beta}{d\lambda} = \frac{c(\lambda_H - \lambda_L)(-\lambda_H\sigma_H^2 + \lambda_L\sigma_L^2 + 2\lambda\sigma_H^2 - 2\lambda\sigma_L^2)}{[(\lambda_H - \lambda_L) + c\lambda(\lambda_H\sigma_H^2 - \lambda_L\sigma_L^2) - c\lambda^2(\sigma_H^2 - \sigma_L^2)]^2}. \tag{10}$$

Proposition 2: In case of a NAM, the resulting equilibrium relationship between agents' risk aversion and the power of the contract incentives is:

A. positive if $\lambda_L \geq \frac{\lambda_H\sigma_H^2}{2\sigma_H^2 - \sigma_L^2}$.

B. negative if $\lambda_H \geq \frac{\lambda_L\sigma_L^2}{2\sigma_L^2 - \sigma_H^2}$ and $2\sigma_L^2 \geq \sigma_H^2$.

C. U-shaped if one of the following two conditions are met:

   a. $\lambda_L < \frac{\lambda_H\sigma_H^2}{2\sigma_H^2 - \sigma_L^2}$, $\lambda_H < \frac{\lambda_L\sigma_L^2}{2\sigma_L^2 - \sigma_H^2}$ and $2\sigma_L^2 > \sigma_H^2$,

   b. $\sigma_H^2 > 2\sigma_L^2$ and $\lambda_L < \frac{\lambda_H\sigma_H^2}{2\sigma_H^2 - \sigma_L^2}$.

Proof: Since the denominator of (10) is always positive, the sign of the derivative depends only on the numerator. In fact, since $c(\lambda_H - \lambda_L) > 0$, the sign of the numerator depends only on the sign of the expression in the parentheses. (A.) The expression in parentheses is positive if $\lambda > \frac{\lambda_H\sigma_H^2 - \lambda_L\sigma_L^2}{2\sigma_H^2 - 2\sigma_L^2}$, from which it is obvious that $\lambda \geq \lambda_L \geq \frac{\lambda_H\sigma_H^2 - \lambda_L\sigma_L^2}{2\sigma_H^2 - 2\sigma_L^2}$, and solving for λ_L gives the stated condition. (B.) The expression in parentheses is negative if $\lambda < \frac{\lambda_H\sigma_H^2 - \lambda_L\sigma_L^2}{2(\sigma_H^2 - \sigma_L^2)}$, from which it is obvious that $\lambda \leq \lambda_H \leq \frac{\lambda_H\sigma_H^2 - \lambda_L\sigma_L^2}{2(\sigma_H^2 - \sigma_L^2)}$. Solving for λ_H produces the first condition, whereas the second condition is simply the requirement that the denominator of the first condition be positive. (C.a.) This case is simply the opposite from the previous two. (C.b.) $\sigma_H^2 > 2\sigma_L^2$ makes $\lambda_H < \frac{\lambda_L\sigma_L^2}{2\sigma_L^2 - \sigma_H^2}$ trivially satisfied and hence not needed. **Q.E.D.**

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Table 1. Summary Statistics: Undocumented Harvest Crop Workers

Variable	Mean	St. Dev.
Piece rate (vs. hourly rate)	0.41	0.49
Average Hourly Wage (2006 U.S. dollars)	7.94	2.09
Female	0.11	0.31
Married	0.51	0.5
Children	0.17	0.37
Age	28.76	9.53
Time in the U.S. (since first entry)	5.94	6.36
Schooling (years)	6.06	3.93
Employed by farm labor contractor (vs. directly by grower)	0.29	0.45
English proficiency (speaking, scale of 1=worst to 4=best)	1.38	0.64
Farm work experience in the U.S.	5.52	5.33
Non-farm employment	0.09	0.29
Weekly hours (farm employment)	41.04	11.9
Full-time	0.78	0.42
Assets in the U.S		
Land	0.002	0.047
House	0.018	0.135
Business	0.001	0.018
Other assets	0.001	0.018
Assets in the home country		
Land	0.111	0.314
House	0.469	0.499
Business	0.002	0.04
Other assets	0.002	0.04
Distance between current residence and current job (miles)		
Located at the job	0.17	0.37
Within 9 miles	0.33	0.47
10-24 miles	0.39	0.49
25-49 miles	0.10	0.31
50-74 miles	0.01	0.09
75+ miles	0	0.03

Table 1 – Cont. Summary Statistics: Undocumented Harvest Crop Workers

Variable	Mean	St. Dev.
Country of birth		
Mexico	0.96	0.18
Central America	0.03	0.18
Elsewhere	0.01	0.06
Crop at the time of the interview		
Field Crops	0.08	0.26
Fruits and Nuts	0.54	0.5
Horticulture	0.03	0.16
Vegetables	0.33	0.47
Miscellaneous	0.02	0.17
Region at the time of the interview		
East	0.13	0.33
Southeast	0.22	0.42
Midwest	0.08	0.27
Southwest	0.03	0.17
Northwest	0.13	0.33
California	0.41	0.49
No. Obs.	3,166	

Note: Authors' calculations based on confidential immigrant harvest crop workers data from the NAWS, 2000-2007.

Table 2. Correlation Matrix among Wealth Assets

	Piece Rate	Land U.S.	House U.S.	Business U.S.	Other U.S.	Land Home	House Home	Business Home	Other Home
Piece Rate	1								
Land in U.S.	0.01	1							
House in U.S.	-0.043	0.317	1						
Business in U.S.	-0.014	0.056	0.06	1					
Other Assets in U.S.	0.001	0.034	0.007	0.027	1				
Land Home Country	0.052	-0.026	-0.07	0.002	0.003	1			
House Home Country	-0.002	-0.096	-0.153	-0.015	-0.01	0.282	1		
Business Home Country	0.021	-0.009	-0.018	-0.003	-0.003	0.07	0.029	1	
Other Assets Home Country	0.019	0.001	-0.001	-0.002	0.082	0.028	-0.005	-0.003	1

Note: Authors' calculations based on confidential immigrant harvest crop workers data from the NAWS, 2000-2007.

Table 3. The Incidence of Piece Rates: Examples

Crop	Piece rate
Olives	1
Oranges	0.95
Parsley	0.85
Grapes Wine	0.65
Grapes Raisin	0.6
Tomatoes	0.45
Peppers, Sweet and Hot	0.45
Cucumbers	0.4
Strawberries	0.25
Spinach	0.2
Grapes Table	0.15
Peaches	0.13
Broccoli	0.03
Christmas Trees	0
Nectarines	0
All crops	0.4

Note: Authors' calculations based on confidential immigrant harvest crop workers data from the NAWS, 2000-2007.

Table 4. Mutinomial Logit: Probability of Choosing Strawberries vs. Oranges

Variable	1	2
Schooling	-0.04	-0.01
	(0.04)	(0.06)
English Proficiency (Speaking)	0.10	0.05
	(0.19)	(0.34)
Female	2.06***	0.76
	(0.34)	(0.54)
Married	0.16	0.04
	(0.22)	(0.37)
Children	0.97***	0.02
	(0.31)	(0.52)
Age	-0.02*	0.00
	(0.01)	(0.02)
Time in U.S.	-0.03	0.01
	(0.04)	(0.08)
Farm Work Experience in U.S. x 10	-0.11	-0.08
	(0.07)	(1.19)
(Farm Work Experience in U.S.)^2 x 10	0.01***	0.00
	0.00	(0.04)
Employed by Farm Labor Contractor	-4.92***	-0.81*
	(0.57)	(0.44)
Non-farm Employment	0.59*	0.04
	(0.32)	(0.68)
Full-time	1.93*	0.10
	(1.11)	(2.00)
Land in U.S.	-41.64	0.09
	(199.54)	(6.83)
House in U.S.	-2.03*	-0.37
	(1.10)	(1.26)
Business in U.S.	1.63	0.37
	(10.40)	(5.83)

Table 4 – Cont. Mutinomial Logit: Probability of Choosing Strawberries vs. Oranges

Variable	1	2
Other Assets in U.S.	-5.78	-3.39
	(193.97)	(10.30)
Land in Home Country	-0.72***	-0.01
	(0.29)	(0.58)
House in Home Country	0.39*	0.02
	(0.20)	(0.34)
Business in Home Country	-105.73	-0.42
	(899.87)	(10.43)
Other Assets in Home Country	9.74	1.26
	(77.15)	(5.43)
Year FE	Yes	Yes
County FE	-	Yes
Log Likelihood	-9,026.59	-12,902.98
No. Obs.	3,166	3,166

Note: Authors' calculations based on confidential immigrant harvest crop workers data from the NAWS, 2000-2007.

Robust standard errors are in parentheses.

* indicates 10 percent significance level; ** indicates 5 percent significance level; *** indicates 1 percent significance level.

Table 5. Contract Equation Estimates: Linear Probability Model

Variable	Piece rate						
	1	2	3	4	5	6	7
Schooling	-0.001	0.000	0.003	0.004	0.002	0.005**	0.005**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
English	-0.03*	-0.04**	-0.05***	-0.04**	-0.03**	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Female	-0.01	0.00	-0.01	-0.02	0.02	0.00	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Married	0.02	0.02	0.02	0.03	0.02	0.03*	0.03**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Children	-0.10***	-0.09***	-0.07**	-0.06**	-0.08***	-0.06***	-0.06***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.003***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time in U.S.	0.003	0.003	0.003	0.001	0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience in U.S. x 10	0.07	0.08	0.103**	0.06	0.085**	0.04	0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)
(Experience in U.S.)^2 x 10	-0.002	-0.002*	-0.002*	-0.001	-0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employed by Contractor	0.26***	0.26***	0.20***	0.18***	0.16***	0.02	0.02
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)
Non-farm Employment	-0.04	-0.04	-0.06	-0.06*	0.00	0.01	0.02
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Full-time	-0.18***	-0.18***	-0.11***	-0.09**	-0.08**	-0.04	-0.04*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)
Land U.S.	0.24	0.23	0.22	0.18	0.31**	0.12	0.13
	(0.18)	(0.18)	(0.18)	(0.17)	(0.14)	(0.11)	(0.11)
House U.S.	-0.05	-0.04	-0.04	-0.02	-0.12**	-0.07	-0.07
	(0.08)	(0.08)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)
Business U.S.	-0.40***	-0.43***	-0.39***	-0.32***	0.13*	0.13**	0.15**
	(0.10)	(0.12)	(0.12)	(0.11)	(0.08)	(0.06)	(0.06)

Table 5 – Cont. Contract Equation Estimates: Linear Probability Model

Variable	Piece rate						
	1	2	3	4	5	6	7
Other Assets U.S.	0.40***	0.39***	0.54***	0.43***	0.59***	0.22**	0.20**
	(0.05)	(0.07)	(0.08)	(0.07)	(0.13)	(0.11)	(0.10)
Land Home	0.13***	0.14***	0.09***	0.09***	0.06**	0.05**	0.05**
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
House Home	-0.06**	-0.06**	-0.03	-0.03	-0.03	-0.02	-0.02
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Business Home	0.39***	0.38***	0.31**	0.25**	0.16*	0.09	0.04
	(0.14)	(0.14)	(0.12)	(0.10)	(0.09)	(0.11)	(0.12)
Other Assets Home	0.02	0.03	0.08	0.03	0.24	0.29	0.30
	(0.30)	(0.30)	(0.32)	(0.31)	(0.34)	(0.31)	(0.32)
Year FE	-	Yes	Yes	Yes	Yes	Yes	Yes
County FE	-	-	-	-	Yes	Yes	Yes
Region FE	-	-	Yes	Yes	-	-	-
Region FE x Time Trend	-	-	-	-	-	-	Yes
Aggregate Crop FE	-	-	-	Yes	-	-	-
Detailed Crop FE	-	-	-	-	-	Yes	Yes
R^2	0.12	0.12	0.21	0.28	0.41	0.60	0.60
No. Obs.	3,166	3,166	3,166	3,166	3,166	3,166	3,166

Note: Authors' calculations based on confidential immigrant harvest crop workers data from the NAWS, 2000-2007.

Robust standard errors are in parentheses.

* indicates 10 percent significance level; ** indicates 5 percent significance level; *** indicates 1 percent significance level.