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Technology Adoption and Risk Preferences: The Case of Machine Harvesting by Southeastern Blueberry Producers

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Abstract

This research investigates the effect of producers' risk preferences on the adoption of a new technology—machine harvesting—among blueberry producers in the Southeastern United States. Technology adoption literature assumes that risk aversion decreases the likelihood of adopting a new technology, but findings reveal that growers with higher levels of risk aversion are more likely to adopt machine harvesting. One explanation for this discrepancy is that we assume there are risks in both forms of harvest technology. The current patchwork or immigration policy and enforcement has made the availability of manual labor—the status quo technology—increasingly volatile.

Keywords: machine harvesting, perennial crops, risk preferences, technology adoption, uncertainty

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Introduction

This research investigates the effect of risk and producer risk preferences on technology adoption and intensity of use of machine harvesting (measured by percentage of machine-harvested acres) among Southeastern commercial blueberry operations. Given current conditions in both the labor regulatory environment and historical harvesting methods, commercial blueberry growers located in the four largest blueberry-producing states in the Southeastern United States were identified as the target population for this study to explore producer risk preferences on the adoption of a new technology. Using theoretical work by Feder (1980), Feder and O'Mara (1981), and Just and Zilberman (1983),[1] we model the decision to adopt machine harvesting and the extent of land allocated to machine harvesting as a function of risk attitudes, the stochastic relationship between the returns of the new and existing technology, and other factors including wealth, farm size, and sources of income. We find that producers that exhibit higher levels of risk aversion are more likely to adopt and use machine harvesting. We also find that increased labor uncertainty has a positive effect on the likelihood of adopting machine harvesting and on the intensity of its use.

Calvin and Martin (2011) analyzed five labor-intensive specialty crops (raisins, oranges, lettuce, strawberries, and asparagus) in the United States. They established differences in machine harvesting-labor substitution across these crops and determined the impact that new legislation would have on that substitution effect. They concluded that uncertainty in labor force availability due to immigration enforcement and new legislation would stimulate farmers to try harvest mechanization; however, responses in adoption, production, and price would vary by commodity. In recent years, the largest blueberry-producing Southeastern states of North Carolina, Georgia, Florida, and Mississippi have proposed statewide legislation affecting immigrant status and enforcement, leading to documented labor shortages and wage volatility among seasonal agricultural laborers (Passel and Cohn, 2012, McCissick and Kane, 2011; Rosson, 2012).

From 2002 to 2011, 69 jurisdictions—including Southeastern counties in North Carolina, Florida, Georgia, and Alabama—adopted Section 287(g) (Kostandini, Mykerezi, and Escalante, 2014).[2] Kostandini, Mykerezi, and Escalante (2014) concluded that counties with Section 287(g) agreements experience declines in farm worker availability. The effect of the resulting increase in labor uncertainty can lead blueberry producers to view the existing, labor-intensive harvesting technology as the riskier option and the new machine-harvesting technology as a risk-reducing option. This represents an important distinction from previous research. Research on adoption of new technology commonly assumes that the new technology (in this case machine harvesting) is the riskier option and the existing technology (labor harvesting) the safer option.

[1] Additional empirical work includes O'Mara (1980); Binswanger et al. (1980); Binswanger (1980); Byerlee and Hesse de Polanco (1986); Marra and Carlson (1987); Kebede (1992); Shapiro, Brorsen, and Doster (1992); Smale and Heisey (1993); Smale, Just, and Leathers (1994); and Abadi Ghadim (2000).

[2] Section 287 (g) of the Illegal Immigration Reform and Immigrant Responsibility Act of 1996 (IIRIRA) allowed federal Immigration and Customs Enforcement (ICE) officials to enter into agreements with local law enforcement officials, such as sheriff's departments, to perform immigration enforcement functions previously exclusively performed by ICE (U.S. Department of Homeland Security, 2014). However, no U.S. counties adopted this section until 2002.

While machinery manufacturers have offered various types of berry-harvesting equipment to the industry since the 1960s, yhese early machine harvesters were designed to shake the berries free of the bush and were most commonly used on the shorter Northern Lowbush (*Vaccinium angustifolium*) variety grown in the northern regions of the United States and Canada to harvest blueberries destined for the processed market. Early machine-harvested blueberries, which were often bruised and smashed, did not require the same quality as fresh market blueberries. As the market for fresh blueberries expanded, research and development into mechanical harvesters sensitive enough for fresh market blueberry species such as Northern Highbush (*Vaccinium corymbosum L.*), Southern Highbush (*Vaccinium corymbosum X darowii*), and Rabbiteye (*Vaccinium ashei*) has increased (Peterson et al., 1997).

While Southeastern cultivated blueberry production started in the late 1960s, commercial-scale operations—which relied on relatively accessible, mostly immigrant workforce for hand harvesting (Martin, 1998)—were establishedin the last two decades. Between 2002 and 2012, total U.S. cultivated blueberry acreage nearly doubled, from 40,820 to 77,700 acres (USDA, 2013a), in response to increased consumer demand, placing added pressure on labor availability. In the four study states (NC, GA, FL, and MS), cultivated blueberry acreage rose from 9,600 to 24,700 acres between 2000 and 2012 (USDA, 2013b), a 157% increase in a region that harvests berries destined primarily for the higher-valued fresh consumer markets.

While nationwide grower fresh prices rose from $1.29/lb to $2.19/lb between 2000 and 2012, it is notable that unharvested blueberries rose from 450,000 pounds in 2007 to nearly 17.5 million pounds in 2013, and another 2.4 million pounds of harvested fruit went unsold. Although experiments with new harvester models have demonstrated a marginally equivalent quality, the technology has not been widely adopted by fresh market blueberry growers in the Southeast. However, recent Southeastern state and county legislation concerning worker verification has led farm workers to migrate out of certain Southeastern states, threatening labor shortages for specialty crop producers (Passel and Cohn, 2012; McCissick and Kane, 2011; Rosson, 2012).

Previous studies have shown that shortages of agricultural workers lead to increases in agricultural worker wages and an increased interest in labor-saving machine technologies (Borjas, 2003; Zahniser et al., 2012). These concerns about labor shortages combined with the newer commercial operations established in this region motivated the need to further understand the potential of mechanical harvesters to reduce risk exposures resulting in higher production input prices and reduced farm profitability.

Feder (1980) developed a theoretical model that incorporates risk preference as an important factor in the technology adoption decision-making process. Other studies (Feder, Just, and Zilberman, 1985; Feder and Umali, 1993; Knight, Weir, and Woldehanna, 2003) have shown the importance of producers' risk preferences on the adoption of new technologies. Marra, Pannell, and Abadi Ghadim (2003) provided an excellent summary of literature on agricultural technology adoption and specifically on the role of uncertainty and risk in the decision-making process, but empirical studies evaluating the effect of producer risk preferences on the adoption of new technologies are limited. Liu (2013) found that more risk-averse Chinese cotton producers would be late adaptors of Bt cotton. Ward and Singh (2014) found that more risk-averse Indian producers are more willing to adopt new risk-reducing, drought-tolerant seeds.

Finally Sanou, Liverpool-Tasie, and Shupp (2015) found that more risk-averse Nigerien producers have a lower likelihood of using fertilizer.

Conceptual Model

A risk-averse farmer may choose to use both new (machine-harvested) and traditional (hand-picked) technologies. A number of key models in the adoption literature present land allocation among technologies as a portfolio selection problem (Feder, 1980; Feder and O'Mara, 1981; Just and Zilberman, 1983). The extent of land allocated to the new technology is determined by risk attitudes, the stochastic relationship between the returns of the two technologies, and the effects of scale factors such as wealth and fixed costs.

Like Just and Zilberman (1983), we assume that producers are risk averse with utility function $U(\cdot)$ defined on wealth and $U' > 0$, $U'' \leq 0$. Further, wealth at the end of the period is assumed to equal the sum of the land value, $p_L\bar{L}$, and the economic profits from production. The producer can allocate all land, $\bar{L}$, to the hand-picked technology or allocate the land between the hand-picked and the machine-harvest technology. In the latter case, the producer will face a new fixed cost, c, for the machine-harvest technology. The producer thus faces a discrete choice ($I \in \{0,1\}$) regarding the investment decision, where I is the adoption indicator (I=1 for adoption of machine-harvest technology and I=0 for nonadoption). Where I=1, the producer faces a continuous choice $\{L_0, L_1\}$ regarding the land-allocation decision, where L_0 and L_1 are the amounts of land allocated to the hand-picked and machine-harvest technology, respectively. The two decisions can be represented by

$$\max_{\substack{I=0,1 \\ L_0, L_1, f}} EU[p_L\bar{L} + \pi_0 L_0 + I(\pi_1 L_1 - c)] \tag{1}$$

$$\text{subject to} \quad \begin{array}{c} L_0 + IL_1 \leq \bar{L} \\ L_0, L_1, f \geq 0 \end{array}$$

where π_0 and $\pi_1 L_1 - c$ are the economic profits per unit of land from the hand-picked and the machine-harvest technology, respectively, and f is the input associated with the machine-harvest technology (machine harvester in this case).

Just and Zilberman (1983) showed that the amount of land allocated to the traditional and new technology is a function of the economic profits for each technology, the variance of the economic profits, and the covariance between the economic profits. This serves as a basis for the specification of the empiric equation to model the producer's continuous decision of land allocation between the two technologies. Additionally, the specification of the empirical model includes other explanatory variables to control for categories defined in Daberkow and McBride's (2003), such as human capital and tenure, risk, credit constraints, production, and agronomic constraints. According to Koundouri, Nauges, and Tzouvelekas (2006), both level of educational attainment and years of experience act as proxies for management abilities and learning and are often correlated, leading to model misspecification. Thus, we use experience variables in our model. Experience variables also measure "learning by doing," which is practical education specific to the farm task that reduces costs and increases the profit differential (Sunding and Zilberman, 2001).

Other variables in the human capital and tenure category include size of household (Fernandez-Cornejo, Hendricks, and Mishra, 2005), plans to transfer ownership to a family member, and a ratio of rented land over total land. Marra, Pannell, and Abadi Ghadim (2003) discussed different approaches used by previous work to measure producer risk preferences. Binswanger et al. (1980) elicited the risk preferences of a sample of Indian farmers using several elicitation techniques, one of which included gambling questions with real monetary pay-offs. In Shapiro, Brorsen, and Doster (1992) producer risk preference was measured by a Pratt–Arrow measure of risk attitude elicited using the method reported in King and Robison (1981). Abadi Ghadim (2000) elicited Arrow–Pratt coefficients of risk aversion based on a set of questions related to hedging. In this research, producer risk preferences were elicited using observed blueberry crop insurance purchases as well as producers' assessment of their willingness to accept risk relative to other blueberry producers. The amount of financed property (Feder, 1980) and income from off-farm activities (Fernandez-Cornejo, Hendricks, and Mishra, 2005) are included to control for the producer's financial position. Production variables include acreage and yield data. Agronomic variables include cultivar and location.

Data and Empirical Model

Data

This study uses cross-sectional data collected from a survey of blueberry producers in the Southeastern United States. A mailed survey instrument was chosen, as answers in mail surveys tend to be the least biased (Salant and Dillman, 1994). We followed the survey method proposed by Salant and Dillman (1994), sending announcement letters, followed by the questionnaire with a cover letter and a return envelope, followed by a reminder postcard, followed by a secondary questionnaire mailing to non-responders.

Prior to the mail survey, researchers personally interviewed eleven blueberry producers representing small, medium, and large-scale commercial operations in each of the study states. Using this feedback, the questionnaire was developed and pre-tested prior to the mailing effort. With assistance from state extension specialists and blueberry associations, 692 commercial blueberry producers were identified in the study area. Of the 692 surveys mailed during July 2011, 234 responded, for a usable response rate of 33.8%. The 2012 Census of Agriculture reported 2,509 blueberry farms in the Florida, Georgia, North Carolina, and Mississippi, thus the 234 survey respondents represented 9.3% of blueberry farms in these states. The 2012 Census of Agriculture also estimated 24,749 acres of tame blueberries in the four selected states. The 234 survey responses represented blueberry acreage of 12,386 acres, which represents 50.0% of total commercial blueberry acreage in the four surveyed states. Our survey data is therefore more oriented toward larger commercial farms than small farms or hobby farms (USDA, 2014).

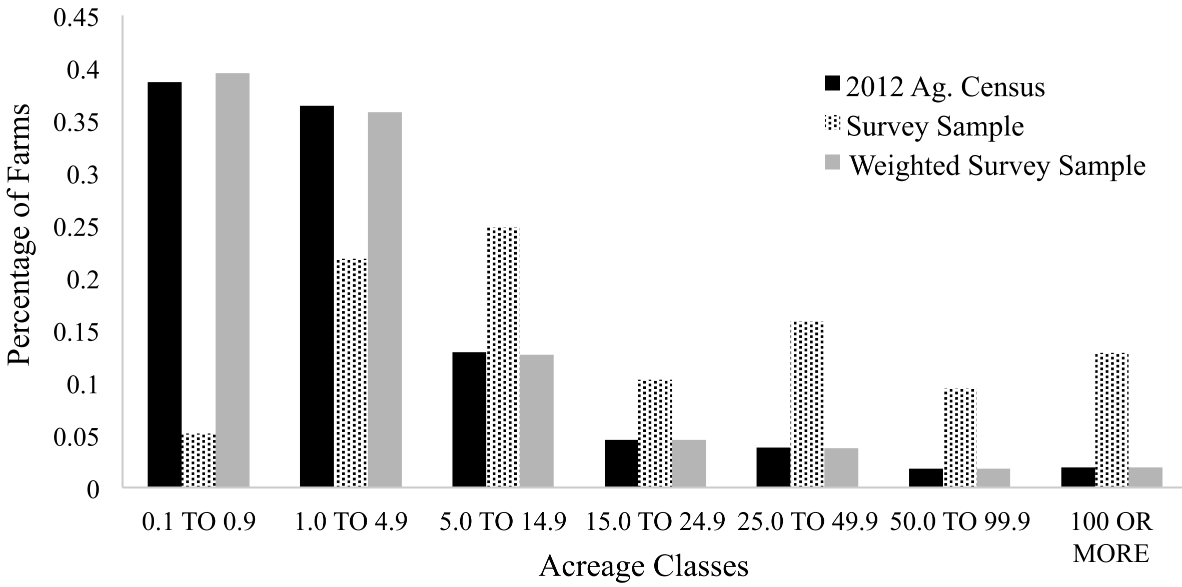

Figure 1. Blueberry Acreage Distribution for the Survey Sample Data Compared with the 2012 Census of Agriculture and the Survey Weighted Sample

Given this response pattern, post-stratified weights (ω) were estimated using the procedure developed by Binder and Théberge (1988). Figure 1 presents the non-weighted and weighted distributions of blueberry acreage for the survey sample. The weighted distribution of the survey responses closely approximates the distribution of blueberry producers for these four states based on the 2012 Census of Agriculture data.

The survey contained 32 questions pertaining to economic conditions, farmer characteristics, production, preferences and perceptions, and social characteristics of their enterprise. Of the 234 responses, 202 were suitable for use in our empirical mode. Summary statistics based on these observations are provided in Table 1.

Survey data were augmented with wage data acquired from The Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW) observed quarterly from 2001 to 2009 (U.S. BLS, 2013). The wage data represents county level annualized weekly wages based on the North American Industry Classification System (NAICS). The wage data were used to derive a historical measure of the average wage and the standard deviation of wage for each county in the study area.

The Economic Research Service (ERS) of the USDA collected data on the average yield per acre for all blueberry farms of the four states in our survey (USDA, 2015). ERS data on average yields for the four states is compared to average yields from our survey data (Table 1). The average yield per acre data reported by our survey respondents is within one standard deviation of the average yield per acre from ERS for the four states, and our four-state average yield data is within a half-ton per acre of the ERS data (Table 2).

Table 1. Summary Statistics of Variables

Variable Name	Variable Description	Mean	Std. Dev.	Min.	Max.
L_1 (percent)	Percent of machine harvested acres	27	39	0	100
I	Adoption of machine harvesting (Yes/No)	0.40	0.49	0	1
PRATIO	Ratio of fresh to frozen grower price received	3.03	1.74	0.52	7.70
SIZE (1,000 lbs./acre)	Farm size in volume of blueberries produced	0.352	0.78	0.0008	4.82
AVGWAGE($)	Annualized weekly farm labor wages (BLS)	493.90	113.94	250.56	843.64
WAGESTD ($)	Standard deviation of annualized weekly farm labor wages	89.47	39.01	32.32	281.96
INS (indicator variable)	Producer has purchased four or more times blueberry insurance in the past ten years	0.28	0.45	0	1
CONCERN_AVG_PRICE	Level of concern about average price received	0.82	0.38	0	1
CONCERN_STAB_PRICE	Level of concern about stability of prices received	0.57	0.50	0	1
EXP (years)	Number of years' experience with blueberry production	11.6	11.6	1	75
OFF_FARM_INCOME (percent)	Percent of total income earned off-farm	59	40	0	100
FINANCED_LAND (percent)	Percent of blueberry land and establishment costs that were financed	21	35	0	100
TRANSFER_OWN (indicator variable)	1 if producer plans to transfer ownership	0.68	0.47	0	1
FAMILY	Number of family members employed in the blueberry operation	3.36	3.99	1	21
GA (indicator variable)	Respondent from Georgia	0.34	0.47	0	1
NC (indicator variable)	Respondent from North Carolina	0.11	0.31	0	1

Table 2. Comparison of Average Commercial Blueberry Yield per Acre Reported by USDA and Survey Respondents for 2010 Harvest

State	2010 ERS Data (Avg. lbs./acre)	2010 Survey Response Data (Avg. lbs./acre)
North Carolina	7,100	6,309 (4,194)
Florida	4,690	6,135 (3,624)
Georgia	4,460	5,124 (3,239)
Mississippi	2,960	5,353 (2,943)
Four state average	4,802	5,730

Source: USDA, 2015.
Notes: Standard deviations reported in parentheses.

The U.S. Federal Crop Insurance Corporation (FCIC) converted a 1995 pilot program into a permanent blueberry crop insurance program in 2005. Our four study states were covered beginning with the 2000 pilot expansion, which informed the survey question related to respondent crop insurance purchases in the previous ten years. In the United States, market penetration for fruit and nut crop insurance coverage held steady from 2000 to 2011 at 73% coverage of commercial acreage. Blueberry crop insurance participation rates were 80% nationwide, and more than 30% of insured acres purchased buy-up insurance in 2011 (USDA, 2013c).

Empirical Model

We model the producer's continuous decision of land allocation using the following empirical model:

$$\begin{aligned} L_{1i} = {} & \beta_0 + \beta_1 PRATIO_i + \beta_2 SIZE_i + \beta_3 SIZE_i * RBBT_i + \beta_4 AVGWAGE_i \\ & + \beta_5 WAGESTD_i + \beta_6 WAGESTD_i * RBBT_i + \beta_7 INS_i \\ & + \beta_8 CONCERN\_AVG\_PRICE_i + \beta_9 CONCERN\_STAB\_PRICE_7 \\ & + \beta_{10} EXP_i + \beta_{11} EXPSQ_i + \beta_{12} OFF\_FARM\_INC_i \\ & + \beta_{13} FINANCED\_LAND_i + \beta_{14} TRANSFER\_OWN_i + \beta_{15} FAMILY_i \\ & + \sum_{l=1}^{2} \beta_{15+l} STATE_{li} + \varepsilon_i \end{aligned} \tag{2}$$

where L_{1i} is the percentage of land harvested using machine harvesting by the ith producer, $PRATIO$ is the ratio of the price for blueberries destined for the fresh market and the price for blueberries destined for the processed market,[3] $SIZE$ is a measure of farm size using production,[4] and $RBBT$ is an indicator variable that takes the value of 1 if the producer grows the Rabbiteye

[3] The price ratio was calculated using prices reported by survey respondents. Additionally, there is little to no variation in the cost of machine harvesters given that there are only two types of blueberry harvesters available. Other costs related to blueberry production are identical for the two technologies.

[4] Using acres as a measure of farm size produced similar results.

variety,[5] $AVGWAGE$ is the average of the county agricultural wage rate estimated using the last ten years of monthly wage rates, $WAGESTD$ is the standard deviation of the county agricultural wage rate estimated using the last ten years of monthly wage rates, which is used to capture the relative riskiness of two technologies serving as a proxy for labor uncertainty possibly due to,[6] among other things, immigration legislation and enforcement (Kostandini, Mykerezi, and Escalante, 2014).

To obtain a measure of producer risk preferences, the survey included a question about the number of times blueberry crop insurance had been purchased in the last ten years.[7] Indicator variables were used to model the responses from this question. INS is an indicator variable that takes the value of 1 if the producer has made four or more blueberry insurance purchases in the last ten years, which was used as a measure of producer level of risk aversion.[8] $CONCERN\_AVG\_PRICE$ is an indicator variable that takes the value of 1 if the producer expresses concern over the average price for the next year, used as a measure of producer concern over the level of returns he/she may obtain in the future. $CONCERN\_STAB\_PRICE$ is an indicator variable that takes the value of 1 if the producer expresses much concern over the stability of the price for the next year, used as a measure of producer concern over the variability of returns. EXP and $EXPSQ$ are the producer experience in growing blueberries and its square (to capture any nonlinearity), OFF_FARM_INC is the percent of producer income from other non-farm sources, $FINANCED\_LAND$ is the percentage of land and establishment costs that are financed, $TRANSFER\_OWN$ is an indicator variable that takes the value of 1 if the producer plans to transfer ownership, $FAMILY$ is the number of family members employed in the blueberry operation, $STATE_1$ and $STATE_2$ are indicator variables for Georgia and North Carolina, respectively, and control for possible regional differences in adoption patterns, and β_0 through β_{17} are the parameters to be estimated.[9]

Given that L_{1i} is potentially bounded by 0 and 1, we use the tobit model (Tobin, 1958) to estimate the regression model specified in equation (2). The log-likelihood and the partial effects (Greene, 2012) are

$$(3) \qquad ln\, l = \sum_{L_i>0} -\frac{1}{2}\left[ln(2\pi) + ln\sigma_\varepsilon^2 + \frac{(L_i - \boldsymbol{x}_i'\boldsymbol{\beta})^2}{\sigma_\varepsilon^2}\right] + \sum_{L_i=0}\left[1 - \Phi\left(\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_\varepsilon}\right)\right]$$

$$(4) \qquad \frac{\partial E[L_i|\boldsymbol{x}_i]}{\partial \boldsymbol{x}_i} = \boldsymbol{\beta\Phi}\left(\frac{\boldsymbol{x}_i\boldsymbol{\beta}}{\sigma_\varepsilon}\right)$$

where the $\boldsymbol{x}$ variables in equations (3) and (4) are as defined in equation (2), σ_ε^2 is the variance of the error term, and $\Phi(\cdot)$ denotes the cumulative density. Marginal effects for discrete explanatory

[5] Most Rabbiteye blueberry varieties have firmer skins and fruit than the Southern Highbush varieties planted in the study region; therefore, they tend to have longer shelf-life and are more commonly mechanically harvested (Braswell, et al., 2009).
[6] We assume constant temporal variation in the cost of machine harvesters for every producer.
[7] The survey also asked producers to rank their willingness to accept risk relative to other blueberry producers. However, using this measure of risk preferences in the regression resulted in reduced model fit as measured by AIC and BIC criteria.
[8] Other indicator variables were not significant.
[9] Nearly all respondents were white males, thus race and sex are not included as socioeconomic variables.

variables and for interaction variables between one continuous variable and one dummy variable are calculated using

$$\text{(5)} \qquad \frac{\partial E[L_i|\boldsymbol{x}_i]}{\partial \boldsymbol{x}_i} = E\left[L_i \middle| \boldsymbol{x}_{ij(d)}, d = 1\right] - E\left[L_i \middle| \boldsymbol{x}_{ij(d)}, d = 0\right],$$

where d is the discrete variable and $\partial E[L_i|\boldsymbol{x}_i] = \boldsymbol{\Phi}\left(\frac{\boldsymbol{x_i\beta}}{\sigma_\varepsilon}\right)\left(\boldsymbol{x}_i\boldsymbol{\beta} + \sigma_\varepsilon \frac{\boldsymbol{\phi}(\boldsymbol{x_i\beta}/\sigma_\varepsilon)}{\boldsymbol{\Phi}(\boldsymbol{x_i\beta}/\sigma_\varepsilon)}\right)$ is calculated at d=1 and d=0 for each observation. The two series of $\partial E[L_i|\boldsymbol{x}_i]$ are then averaged and the marginal effect for the discrete variable is calculated as the difference between the averages. Marginal effects for variables that have a quadratic term were calculated using

$$\text{(6)} \qquad \frac{\partial E[L_i|\boldsymbol{x}_i]}{\partial \boldsymbol{x}_i} = \left(\beta_l + 2\beta_q x_{ij}\right)\boldsymbol{\Phi}\left(\frac{\boldsymbol{x_i\beta}}{\sigma_\varepsilon}\right),$$

where β_l is the coefficient for the linear term and β_q is the coefficient for the quadratic term. The marginal effects for these variables are calculated as the mean of the marginal effect for each observation.

The tobit model in equation (3) is considered a special case of the more general two-step model (Greene, 2012), where the first step models the probability of adoption, which is also independent of the intensity of use of the technology modeled in the second step. We test this restriction using the Lagrange multiplier (LM) test discussed in Greene (2012). The test statistic calculated as LM = 2*(lnL_{tobit} – (lnL_{probit} + $lnL_{truncated}$)) has a Chi-square distribution, and lnL_{tobit}, lnL_{probit}, and $lnL_{truncated}$ are, respectively, the log likelihood values from the tobit model, the probit model of the adoption decision, and the truncated regression model using only observations with positive number of acres that are machine harvested.

In addition to the tobit model, we also estimate the fractional response regression proposed by Papke and Wooldridge (1996).[10] In this model, the dependent variable is bounded between 0 and 1 by imposing a link function $G(\cdot)$, such as a logit or log-log transformation function:

$$\text{(7)} \qquad E[L_i|\boldsymbol{x}_i] = G(\boldsymbol{x}_i\boldsymbol{\beta}).$$

The quasi-likelihood estimator of $\boldsymbol{\beta}$ is obtained by maximizing the log-likelihood function as given by

$$\text{(8)} \qquad lnl = \sum_i (L_i logG(\boldsymbol{x}_i\boldsymbol{\beta}) + (1 - L_i)log(1 - logG(\boldsymbol{x}_i\boldsymbol{\beta}))).$$

Results

Using the LM statistic to test the tobit restriction against the two-step model that considers the probability of adoption as independent of the intensity of use of the technology, we obtain LM

[10] Results for the fractional response regression are available from the authors upon request. The results are similar to the results from the tobit regression. We do not report these results here as they are generally inferior to the tobit regression results in terms of model fit as measured by the AIC/BIC criteria.

19.86 and a respective probability for a Chi-square distribution with 17 degrees of freedom of 0.282. Therefore, we fail to reject the tobit restriction.[11]

Regression coefficients of the tobit model, associated standard errors, and significance levels are presented in Table 3, along with the marginal effects and standard errors derived using the delta method. Table 3 reports results for both non-weighted and weighted regression models. The weighted regression uses the post-stratified weights (ω) described earlier and provides a better fit as indicated by the log-likelihood value. The signs and magnitudes of the marginal effects are similar across the non-weighted and the weighted regression models. The price ratio (fresh price/processed price) negatively affects the use of machine harvesting. Since blueberries from machine harvesting are primarily destined for processing, a higher price for fresh blueberries relative to the price for blueberries for processing would result in reduced or no use of machine harvesting. The effect of farm size for producers of both Highbush and Rabbiteye varieties is not statistically significant in the non-weighted regression but becomes significant when post-stratified weights are applied. Given that larger producers are more likely to respond to technology adoption surveys,[12] it is important to account for this sample bias by using post-stratified survey weights.

The average wage rate and the standard deviation of wage rate also have no statistically significant effect on the use of machine harvesting.[13] However, when interacted with a dummy variable for Rabbiteye production, the standard deviation of wage rate has a significant positive effect on the use of machine harvesting. The marginal effect implies that a one dollar increase in the standard deviation of the weekly wage increases the percentage of land under machine harvesting for Rabbiteye production by 0.0043 percentage points (0.0098 percentage points based on the weighted regression results). This finding supports the hypothesis that the effect of increasing farm labor uncertainty due to recent legislative initiatives in the Southeast may have led blueberry producers to view the current labor-harvesting technology as the riskier option and the new machine-harvesting technology as a risk-reducing option.

Frequency of blueberry insurance purchases and concern about the stability of price serve as measures of producers' risk preferences. Producers who more frequently buy crop insurance and have higher concerns about price stability, indicating higher levels of risk aversion, are more likely to use machine harvesting at higher intensity. These effects are as expected under the hypothesis that the machine-harvesting technology is considered the safer (less risky) option. Concern about the average price for the season measures producers' attitude toward the profitability of their operation. Producers who have higher concerns about average price are

[11] We report the results of the probit regression modeling the decision to adopt machine harvesting and the truncated regression modeling the intensity of use of machine harvesting in Appendix Tables A1 and A2. Results of Tables A1 and A2 are consistent with the tobit results reported in Table 3 and the tobit restriction, in the sense that the direction of the effect for each regressor on both, the decision to adopt, and the intensity of use of machine harvesting are the same. One result to highlight is that farm size has a positive and significant effect on the intensity of use of machine harvesting, particularly for producers that grow Rabbiteye varieties. This finding is similar to the tobit results based on the weighted sample that adjusts for the bias in the higher response rate from larger producers. Additionally, farm size has a positive and significant effect on the decision to adopt machine harvesting, but only among producers that grow Rabbiteye varieties. Finally, plans to transfer ownership have a significant negative effect on the decision to adopt machine harvesting.

[12] The authors appreciate the suggestions of one of the anonymous reviewers.

[13] We investigated using wages for the last available year (2009) and obtained similar results.

Table 3. Tobit Model Results of Machine Harvest Adoption and Intensity of Use for the Non-Weighted and Weighted Sample

	Non-Weighted Sample			Weighted Sample		
Variable	**Coeff.**	**Std. Err.**	**Marginal Effect**	**Coeff.**	**Std. Err.**	**Marginal Effect**
INTERCEPT	-0.413	0.334		-0.443	0.708	
PRATIO	-0.128***	0.035	-0.0613***	-0.102**	0.049	-0.0495**
SIZE	0.160	0.214	0.0763	1.029**	0.564	0.3956**
SIZE*RBBT	-0.168	0.213	-0.0804	0.728**	0.357	0.2875**
AVGWAGE	-0.0004	0.0005	-0.0002	-0.0004	0.001	-0.0002
WAGESTD	-0.004	0.003	-0.0018	-0.003	0.008	-0.0011
WAGESTD*RBBT	0.009***	0.002	0.0043***	0.025***	0.007	0.0098***
INS	0.187**	0.099	0.0893*	0.263*	0.173	0.1017*
CONCERN_AVG_PRICE	0.285*	0.175	0.1361*	0.414*	0.216	0.1601*
CONCERN_STAB_PRICE	0.230**	0.107	0.1096**	0.404**	0.189	0.1606**
EXP	0.019**	0.009	0.0093**	0.004	0.017	0.0015
EXPSQ	-0.0002*	0.000		-0.000	0.000	
OFF_FARM_INCOME	-0.244**	0.122	-0.1164*	-0.160	0.254	-0.0620
FINANCED_LAND	-0.055	0.133	-0.0264	-0.021	0.217	-0.0083
TRANSFER_OWN	-0.106	0.112	-0.0508	-0.263	0.196	-0.1018
FAMILY	0.0003	0.011	0.0001	0.002	0.019	0.0009
GA	0.711***	0.116	0.3394***	0.981***	0.272	0.3791***
NC	0.485***	0.178	0.2315***	0.605*	0.383	0.2340*
SIGMA	0.365***	0.035		0.434***	0.071	
Number of Observations	133			133		
Log Likelihood	-42.69			-22.37		

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

more likely to use machine harvesting at higher intensity. This finding can be explained by the fact that once northern states hit peak production in the summer months, supplies overwhelm the fresh market, average grower prices received decrease, and the cost of hand-picking is too high to justify continued labor harvesting. While nominal grower fresh prices increased during the study period, nearly 5% of 2013 fruit volume was either unharvested or unsold, perhaps as a result of pressure on labor availability and increased fruit volumes due to nationwide doubling of blueberry acreage that reached 2013 markets. Producers see adoption of machine harvesting as a way to reduce variable costs and minimize the problems associated with finding pickers.

The coefficient for number of years' experience with blueberry production shows increased intensity of use of machine harvesting with more experience. However, the negative sign of the quadratic term reveals that the rate of use decreases as the producer reaches a certain number of years of experience. The inflection point was calculated to be 43 years. Higher levels of off-farm income, implying reduced importance of blueberry production to the producer's financial well-being, result in lower intensity machine harvesting use. Producers in Georgia and North Carolina have higher intensity of use of machine harvesting compared to producers in Florida and Mississippi. One reason for this may be recent developments with respect to immigration, like the signing into law in 2006 of the Georgia Security and Immigration Compliance Act (SB 529) which created the Southeast's strictest state-led immigration enforcement legislation.

It is possible that the inclusion of some decision variables — like farm size and off-farm income —as explanatory variables may lead to an endogeneity problem. We believe that the decision on farm size and off-farm employment is not simultaneous with the decision to adopt and use machine harvesting. However, to provide a robustness check, we perform the two-step endogeneity test proposed by Smith and Blundell (1986) and described in Wooldridge (2010). In the first step, OLS regressions are estimated by regressing the possible endogenous variables, farm size and off-farm income, against all other exogenous variables. Additional exogenous variables included in the OLS regressions were an indicator variable for Florida, education, and age of the producer. In the second step, residuals for size and off-farm income from the first-step OLS regressions are included as additional explanatory variables in the tobit regression. The *t* statistic on the residuals reported by the tobit model provides a simple test of the null hypothesis that size and off-farm income are exogenous (Wooldridge, 2010). Results of the endogeneity test in the second-step tobit estimation are reported in Appendix Table A3. The coefficients for both residuals are not significant, indicating that endogeneity may not be an issue in this case.

Conclusions

This research adds to the empirical work dedicated to measuring the effect of producers' risk preferences in the adoption and use of a new technology. We employ the theoretical work of Feder (1980), Feder and O'Mara (1981), and Just and Zilberman (1983) to model the decision of blueberry producers in the Southeastern United States to adopt machine harvesting and the extent of land allocated to machine harvesting as a function of risk attitudes, the stochastic relationship between the returns of the new and existing technology, and other factors such as wealth, farm size, and sources of income.

Given recent legislative developments with regard to immigration status and enforcement in the largest blueberry-producing Southeastern states of North Carolina, Georgia, Florida, and Mississippi and the resulting labor shortages and wage volatility, we also investigate the effect of labor uncertainty in the adoption and use of machine harvesting among blueberry producers. While technology adoption literature assumes that risk aversion leads to a decreased likelihood of adoption of a new technology, our analysis reveals that Southeastern blueberry growers who exhibit higher levels of risk aversion are more likely to adopt and use machine harvesting. One explanation for this discrepancy between our analysis and previous technology adoption literature is that our analysis assumes that there are risks in both forms of harvest technology. The status quo technology for blueberry harvesting is manual labor; due to the current state of patchwork immigration policy and enforcement, labor availability is becoming more volatile. Conversely, new machine-harvesting technology is still economically unproven for many of the premium price Southeastern blueberry cultivars.

We find that increased labor uncertainty has a positive effect on the likelihood of adopting machine harvesting and on its intensity of use. This finding supports the hypothesis that Southeastern blueberry producers may view the machine-harvesting technology as a risk-reducing technology compared to the current technology of labor harvesting. We also find that blueberry producers who express higher levels of concern regarding both the average grower price received and the stability of grower prices received are more likely to adopt machine harvesting and use it at a higher intensity. Our results regarding the factors that affect the adoption and use of machine harvesting have implications for both blueberry producers and policymakers in states that produce blueberries and other specialty crops.

Our findings may be useful to machine harvester dealers looking to expand market coverage in the Southeastern blueberry production regions given the large increase in acreage and continued uncertainty surrounding farm labor access and availability. Producers are encouraged to consider the financial implications of investment in machine harvest equipment relative to labor costs as a risk management option, viewed through the lens of individual operation scale, labor access situation, blueberry variety and planting arrangements, and current farm financial conditions. For many mid- to large-size Southeastern perennial fruit operations, federal, state, and local policies related to farm labor wages and other key employment conditions have resulted in grower adoption of innovative technological advantages. This research may be used to inform policymakers of the impact of restrictive immigrant farm labor policies on the blueberry industry and related market supply conditions.

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Appendix

Table A1. Probit Model Results of Decision to Adopt Machine Harvesting

Variable	Coefficient	Std. Error	Marginal Effect
INTERCEPT	-2.490	1.784	
PRATIO	-0.395**	0.199	-0.0374
SIZE	0.777	1.290	0.0856
SIZE*RBBT	17.670***	6.621	0.236***
AVGWAGE	0.007	0.004	0.0008
WAGESTD	-0.030	0.028	-0.0033
WAGESTD*RBBT	0.018**	0.009	0.0020*
INS	1.879**	0.119	0.2068**
CONCERN_AVG_PRICE	1.797**	1.129	0.1980**
CONCERN_STAB_PRICE	1.308***	0.677	0.1440***
EXP	0.574***	0.229	0.0637**
EXPSQ	-0.021***	0.008	
OFF_FARM_INCOME	-1.070	0.756	-0.1177
FINANCED_LAND	-1.278	0.878	-0.0407
TRANSFER_OWN	-1.798***	0.635	-0.1979**
FAMILY	0.041	0.066	0.0045
GA	2.136***	0.731	0.2351***
NC	2.865**	1.118	0.2517**
Number of Observations	133		
Log Likelihood	-24.23		

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

Table A2. Truncated Regression Results for Intensity of Use of Machine Harvesting

Variable	Coefficient	Std. Error	Marginal Effect
INTERCEPT	0.276	0.279	
PRATIO	-0.034*	0.021	-0.0322*
SIZE	0.744***	0.269	0.7054***
SIZE*RBBT	0.695***	0.245	0.659***
AVGWAGE	-0.0005	0.0003	-0.0004
WAGESTD	0.010***	0.003	0.0092**
WAGESTD*RBBT	0.006**	0.003	0.0059*
INS	0.048*	0.034	0.0461*
CONCERN_AVG_PRICE	0.070	0.181	0.0664
CONCERN_STAB_PRICE	0.011	0.088	0.0105
EXP	0.009*	0.005	0.0080*
EXPSQ	-0.001	0.008	
OFF_FARM_INCOME	-0.036	0.094	-0.0337
FINANCED_LAND	0.037	0.105	0.0352
TRANSFER_OWN	0.047	0.098	0.0455
FAMILY	0.006	0.009	0.0062
GA	0.332***	0.108	0.3158***
NC	0.104	0.168	0.0983
SIGMA	0.238***	0.023	
Number of Observations	61		
Log Likelihood	-8.53		

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

Table A3. Robustness Check of the Regression Results for Possible Endogeneity

Variable	Coefficient	Std. Error
INTERCEPT	-0.501	0.676
PRATIO	-0.134***	0.035
SIZE	0.082	0.624
SIZE*RBBT	-0.223	0.209
AVGWAGE	-0.0005	0.0005
WAGESTD	-0.004	0.003
WAGESTD*RBBT	0.009***	0.002
INS	0.184**	0.120
CONCERN_AVG_PRICE	0.308*	0.185
CONCERN_STAB_PRICE	0.203**	0.107
EXP	0.014**	0.009
EXPSQ	-0.0001	0.009
OFF_FARM_INCOME	-0.307**	0.154
FINANCED_LAND	-0.118	0.136
TRANSFER_OWN	-0.126	0.139
FAMILY	0.000	0.011
GA	0.765***	0.147
NC	0.448***	0.213
SIZE_RESIDUALS	-0.216	0.348
OFFFARM_RESIDUALS	1.098	0.796
SIGMA	0.356***	0.034
Number of Observations	133	
Log Likelihood	-40.98	

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.