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Determining Willingness To Adopt Mechanical Harvesters Among Southeastern Blueberry Farmers

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By

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Determining willingness to adopt mechanical harvesters among Southeastern blueberry farmers

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Recent technological innovations allow Southeastern blueberry farmers to machine harvest highly profitable fresh-market berries with marginally equivalent quality as labor intensive hand harvesting, drastically reducing labor costs while minimally increasing equipment costs. Concurrent with these innovations, 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. Using survey information, this study uses ex-post and ex-ante logit regression models to determine if machine harvester technology (MHT) adoption is explained by human capital variables, production differences, risk preferences, wage variability, regional differences and differences in Southeastern blueberry cultivars. Ex-post results conclude that experience, production increases, observed measures of risk-averse preferences, increased wage variation, and regional differences explain current MHT adoption in the Southeast. Ex-ante results conclude regional differences explain future consideration of MHT adoption likelihood.

DEDICATION

I dedicate this work to my wife for her unconditional encouragement, my newborn daughter for her unconditional love, my mother for teaching me the value of learning, and my father teaching me the value of farming.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

An Associated Press article published in the summer of 2013 highlighted the fact that the value of blueberry production in Georgia had increased well past peaches, the state's historically celebrated fruit crop. This increase in production value parallels a threefold increase in U.S. blueberry consumption over decade to 1.3 pound per capita per year (Perez et al., 2011). Likewise, exports of U.S. grown blueberries have tripled over the same time frame (Perez et al., 2011). Due to substantial increases in demand, blueberry production has vigorously expanded in the Southeast region and now represents about 27 percent of the total blueberry production for the entire U.S. (ERS, 2010). The Southeast region is well adapted to blueberry production due to warm winter climates and soil typology. Because of these geographical characteristics and increasing demand, the blueberry industry in the Southeast region has experienced a fourfold increase in production since 2000 (Morgan, et al. 2011).

High value or specialty crops farms (fruits, vegetables, tree nuts, nursery and greenhouse products) represent only 7% of all U.S. farms but account for 52% of total hired farm labor hours (Fisher and Knutson, 2012). This discrepancy is driven by the labor intensiveness of high value crop production, especially during harvesting (Calvin and Martin, 2011). Fresh blueberry production in the Southeast region is generally characterized by hand harvesting, with some estimates of harvesting costs being as high as 58.5% of gross receipts (Fonsah et al., 2007). This high cost is due to the rather large workforce needed to hand pick each acre of blueberries over a 4 to 6 week ripening window, with labor estimates as high as 590 worker hours per acre (Brown et al. 1983).

Like other specialty crops, machine harvesters for blueberries have been a focus of manufacturers since the 1960s. Early machine harvesters were designed to shake berries free of the bush and were most commonly used on the shorter Northern Lowbush (*Vaccinium angustifolium*) cultivar grown in the northern regions of the U.S. and Canada and used for processed blueberries. These early machine harvested blueberries, often bruised and smashed, did not need to have the same quality as fresh market blueberries. As the market for fresh blueberries expanded, research and development into harvesters that are sensitive enough to handle fresh market cultivars such as Northern Highbush (*Vaccinium corymbosum L.),* Southern Highbush (*Vaccinium corymbosum X darowii*) and Rabbiteye (*Vaccinium ashei*) has increased (Petersen et al., 1997). Although these newer harvesters vastly reduce harvest labor hours and recent experiments have shown to harvest berries at a marginally equivalent quality, they have not been widely adopted by fresh market blueberry growers, especially in the Southeast (Morgan et al., 2011).

For most of the 50 year history of cultivated blueberry production in the Southeast, there has been a relatively accessible, mostly immigrant workforce for hand harvesting (Martin, 1998). However, recent Southeastern state and county legislation concerning worker verification has led to a migration of farm workers out of certain Southeastern states, and has increased concerns regarding labor shortages among specialty crop producers (Passel and Cohn, 2011, McCissick and Kane, 2011; Rosson, 2012). Previous studies have shown that labor shortages lead to increases in agricultural worker wages and, thus an increased interest in labor saving machine technologies (Borjas, 2003; Zahniser et al., 2008).

The question is then raised as to what are the economic motivations for adopting machine harvesting technology among blueberry farmers in the Southeast, with a primary focus on labor uncertainty and risk perceptions. This thesis investigates factors that influence a blueberry farmer's adoption of machine harvesting technology as a substitute for hand harvesting. Identification of these influential factors, especially related to labor uncertainty and risk preferences, provides insight into motivations for adoption of machine harvesting technology.

CHAPTER II

BACKGROUND OF SOUTHEASTERN BLUEBERRY INDUSTRY

Introduction

This chapter is divided into four subsections pertaining to the Southeastern blueberry industry and available harvesting technologies. The first subsection is a brief introduction to Southeastern blueberry production. The second subsection concerns hand and mechanical blueberry harvesting. The third section pertains to post-harvest blueberry markets. And, the fourth section is a brief history of farm labor, immigration, and harvest mechanization in the Southeast from the middle of the 20th century to the present.

Southeastern Blueberry Production

The two main blueberry cultivars grown in the U.S. Southeast are Rabbiteye (*Vaccinium ashei*) and Southern Highbush (SHB, *Vaccinium corymbosum X darrowii)*. Varieties of these cultivars are selected based on the number of chilling hours needed (hours under 45° F. per dormancy period), soil acidity and typology, terrain, and farmer preference (Braswell, 2009). Once necessary chilling hours are received by the plant, flower development starts, but the fruiting process is now very sensitive to temperatures below 32 °F. Most blueberry cultivars are self-sterile, so blueberry orchards are generally planted with two or more varieties in various patterns in order to improve pollination and fruit set. Farmers will normally decide on these two varieties based on similar chilling hour restrictions or soil preferences, as well as strong pollination capabilities. These agronomic characteristics must be acknowledged by the growers in order to determine their expected price per pound in the open market.

Rabbiteye Cultivar

Rabbiteye blueberries are native to the Southeastern U.S. and are generally considered more vigorous in the native, well drained, pine-belt soils. They are well adapted to highly acidic (pH 4.5-5.5) soils that are common to old farmland or harvested pine forests, and require relatively little organic matter. Rabbiteye orchard life is between 10 to 15 years of high production using good management practice. Thus, a typical orchard has a total life of 20-25 years with 5 years from planting until full production, and 5 years of declining production as soil organic matter depletes and plant health deteriorates. A rabbiteye orchard is recommended to be planted 5 feet apart in 12 foot rows for a total of 726 plants per acre. A well-managed rabbiteye orchard will yield between 6,000 and 10,000 lbs. /acre per year in its prime production years. Most rabbiteye blueberry varieties have firmer skin and fruit than SHB cultivars. Therefore, they tend to have longer shelf-life and are more commonly mechanically harvested than SHB (Braswell, et al., 2009). Most rabbiteye producers develop their orchards with the lowest chilling hour varieties that are suitable for their climate in order to harvest as early as possible (further discussed in the Blueberry Industry section). Rabbiteye varieties in the Southeast mature from April to August, with the Florida market harvesting first and the North Carolina market harvesting last (Braswell, et al. 2009; Safley, Cline, and Mainland, 2006).

Southern Highbush Cultivar (SHB)

SHB cultivar is a result of breeding between the Northern Highbush (*V. Corymbosum*) and the native southern species. This breeding resulted in a cultivar that has the early ripening traits of the Northern Highbush with the adaptations to Southern terrain, soil typology and climate. A SHB orchard requires more care and closer management than a Rabbiteye orchard. SBH demands more organic matter per acre before planting and is more sensitive to low pH levels. SHB varieties are not as vigorous as their Rabbiteye counterparts although they will have the same orchard life of about 20 to 25 years. The planting schedule for SHB is 4 feet apart in 10 foot rows because SHB plants tend to be smaller than Rabbiteye, although some producers are adopting a 2.5 foot by 10 foot schedule. This planting schedule results in 1,089 plants per acre to 1,742 plants per acre depending on spacing. Pounds per acre of SHB range from 3,000 to 8,000 depending on management, irrigation, soil typology, and fertilization. Many SHB varieties have fruit that is larger, sometimes penny size, than Rabbiteye varieties, and tend to have softer flesh and fruit that is often preferable to fresh market consumers. SHB ripens earlier and is available for market from March to early June in the Southeast (Braswell, et al. 2009). Mechanical harvesting of SHB varieties is not as common as Rabbiteye, as the fruit is more susceptible to bruising (Braswell, 2009; Fonsah et al., 2013).

Blueberry Harvesting and Post-Harvest

The harvesting method each blueberry producer uses often coincides with the expected market for those blueberries. Blueberry orchards need to be picked every 5 to 7 days during the harvest season to optimize size and flavor. Therefore, blueberry orchards in the Southeast are usually picked 3 to 5 times throughout the harvest season. There are two methods of harvesting blueberries: hand picking and machine harvesting. Hand picking blueberries is labor intensive because blueberries take considerably more time per acre to pick than many other hand-picked crops. Each mature bush is covered in hanging clusters of five to 100 berries, and needs to be individually picked according to ripeness (clusters may have varying degrees of ripeness) without bruising or popping the skin. Each bush can reach 12-15 feet in height and 10 feet in diameter, making hand picking labor intensive due to pickers needing to go up and down ladders. The fruit for the commercial fresh market cannot be picked at its peak ripeness, nor excessively handled, because it will lose its surface wax called "bloom" and dramatically reduce store shelf life (Braswell et al., 2009; Giles, 2013). Hand-picked blueberries are most likely destined for the fresh market, where they receive a higher price per pound than the processed market; however, if the fresh market is saturated, Southeastern farmers will reluctantly hand pick for the processed market (Safley, Cline, and Mainland, 2006).

Due to the amount of hours needed to pick each acre of blueberries, the price of labor is a factor in the farmer's harvesting technology decision. According to the National Agricultural Workers Survey, Southeastern hourly agricultural field worker wages increased from $6.52/hr in 2001 to $8.53/hr in 2009. These wages maintained around a $1.50/hr increase above the federal minimum wage over a nine year span with the federal minimum wage of $5.15/hr in 2001 to $6.55/hr in 2009 (Department of Labor, 2010). Availability of labor is also a factor in the farmer's harvesting decision and will be further addressed in the following subsections.

Mechanical harvesting of blueberries was first introduced on the smaller and thicker fleshed Northern Lowbush cultivars (*V. angustifolium*). However, innovations in harvesting technology have generated machines that are capable of harvesting the bigger SHB and rabbiteye cultivars. The machines need to be run every 5-7 days with 3 to 5 passes through the orchard on the same schedule as hand-picking. There are a variety of harvesting machines, including over the row harvesters and catch frame harvesters, such as the OXBO Korvan 8000 or OXBO Korvan 7420 respectively, or harvesters that use specialized vacuums to blow off the ripe berries, such as the Blueberry Equipment Inc. (BEI) Black Ice. The first two harvesters use finger-like tines to beat the berries off the bush and catch them as they fall; the last harvester uses a circular air motion to knock the berries off into a basin. Once the berries are off the bush, grading and sorting must occur as sticks, leaves, and un-ripened berries also end up being picked (Huffman, 2012).

Loss of fruit, fruit bruising, and delayed harvesting are all disadvantages of using a machine harvester. Harvesting machines are inferior to hand-picking in terms of discerning between ripe and unripe berries, and unripe "reds" and "greens" will often come off the bush prematurely and must be sorted out. Once the fruit is knocked off the bush, harvesting machines have conveyor belt catchment basins to move the fruit into flats for sorting. However, fruit often misses the catchment basins and falls to the ground around the canes. Blueberry bushes must also fit in the size parameter specifications of the specific machine harvester. In order to meet these specifications, mature bushes need to be pruned often decreasing their fruit bearing canopy. Fruit loss associated with unripe fruit, dropping, and pruning can reach 30% of total yield (Takeda, et al. 2013; Mainland, 1993). Harvesting machines also bruise berries more than hand picking. The mechanical tines used to knock off the fruit are not as sensitive as a typical field worker picking, and mechanically removed berries fall 12 to 48 inches onto the hard plastic fish scales of the catchment basins. The tines and the falling causes increased fruit bruising which decreases the pack-out percentage of fruit that meets the U.S. No. 1 grade standard of the USDA, which in turn decreases farm gate prices as lower grade (bruised) berries have a shorter shelf life. Because mechanical harvesters frequently knock off "reds" and "greens" growers have a tendency to delay harvesting by five to seven days. This week delay can cause a lower farm gate price for the growers in the time sensitive early season, and can lead to excessive overripe berries towards the end of harvest increasing fungal risks (Takeda, et al., 2013).

Due to these mechanical harvesting complications, the majority of machine harvested blueberries go to the processed market where bruising and popping are not as big a deterrent for purchasing. However, some blueberry farmers have recently started machine harvesting for the fresh market in order to capture higher farm gate prices at lower harvesting costs (Takeda et al, 2008). Studies have recently been conducted on fresh market machine harvesting of SHB and Rabbiteye with machines such as the V45 or the BEI International Black Ice, showing lessened likelihood to cause fruit bruising and popping (Takeda et al., 2008; Huffman, 2012). Currently, research institutions have started to develop early ripening SHB varieties with thicker skin and less sensitivity to bruising with the intention that they would be used in a machine harvesting setting (Morgan et al., 2011; Takeda, et al., 2013).

A new machine harvester, depending on the functionality, costs between \$100,000 and \$200,000 with a useful life of less than 20 years. Maintenance costs and upkeep are undetermined (Giles, 2013; Huffman 2012). However, as the price for the harvester is amortized over that 20 year life span, the costs for machine harvesting is estimated at $5.67/flat for fresh market and $0.39/lb. for processed market, contrasted with $8.29/flat for fresh market and $0.72/lb. to $0.83/lb. for processed market using hand harvesting (Safley, Cline, and Mainland, 2006; Fonsah et al., 2013).

Post-harvest often requires fans and air conditioning in order to dry the berries to reduce fungus and cool the berries in order to slow ripening. Grading is also done by hand, sorting by color and removing leaves, twigs, and berries with broken skins. However, excessive hand grading is frowned upon due to the removal of the "bloom" and the possibility of sanitary contamination because blueberries are often not washed in the harvest or post-harvest process. Recently, graders and sorters that use precision technologies such as laser optics that can distinguish specific colors of blueberries have been developed as a substitute for hand sorting and grading (Giles, 2013; Braswell et al., 2009). The economic benefits of hand harvesting versus machine harvesting blueberries include higher farm-gate prices per pound and higher yields, but costs per pound are also high. This information is widely acknowledged in current Southeastern blueberry enterprise budgets.

Blueberry Market

The price per pound for hand-picked fresh market blueberries declines as the harvest season progresses throughout the year. Hand-picked, fresh market Southern Highbush blueberries from Florida (with the earliest ripening time, lowest chilling hours) receive the highest fresh market price at the beginning of the harvest season, generally around March (Williamson and Lyrene, 2004). As other regions in the Southeast begin to harvest their Southern Highbush, generally between April and May, the price per pound for hand-picked fresh market blueberries starts to decline. Although March, April, and May are considered traditionally high value months for Southeastern growers, recent North American plantings have expanded early season volume, decreasing farm gate prices during those months (Takeda, et al., 2013).

Rabbiteye harvest season begins in May and June in the Southeast and the market for fresh blueberries starts to show signs of crowding and a decline in fresh blueberry farm-gate prices (ERS, 2010). As other blueberry growing regions such as New Jersey, Michigan, Oregon, and California begin to harvest in the late summer, the price per pound on the fresh market further declines. By late summer, commercial Southeastern blueberry producers who are still harvesting will shift to the lowest cost harvest practice, regardless of the low price per pound due to the domestic glut, and sell their product to the processed market to finish the season. Thus, a profit maximizing blueberry producer will try to produce the most fresh market yield as early in the season as possible (Morgan et al., 2011; ERS, 2010).

Due to the demand for fresh market blueberries, international producers have expanded to provide fresh blueberries year round within the U.S. South America has increased blueberry acreage 1,246% and Europe has increased acreage 325% from 1995 to 2008 (Hummel et al., 2012). However, neither product competes directly with the domestic fresh blueberry market. South American blueberries are primarily imported during the domestic blueberry off season, November through February, and European blueberries generally stay on the Eurasian continent (Hummel et al., 2012).

Southeastern Blueberry Farmworkers

Martin (2013) estimated that of the 2.6 million workers directly hired by U.S. farm operators in 2007, two thirds are seasonal workers, working less than 150 days on their corresponding farm. Of those seasonal farmworkers, three quarters work in the fruit, vegetable, and horticulture (FVH) industry. Calvin and Martin (2011) used U.S. Department of Labor's National Agricultural Workers Survey (NAWS) to estimate that from 2005 to 2007, 52% of hired workers in agriculture were unauthorized immigrants, and 21% were authorized immigrants in self-reported data. However, Hertz and Zahniser (2013) reports that within just the fruit and nut industry in 2007, 67% of hired workers were legally unauthorized to work in the U.S., including 97% of new entrants (less than two years in U.S. farm labor). While these unauthorized workers were once concentrated in states such as California and Oregon, Passel and Cohn (2009) state that unauthorized workers can be found in high concentrations in any U.S. state with FVH operations, with the largest percentage growth in unauthorized workers in the Southeast and Midwest.

Recently released Congressional testimony (Levine, 2009) has estimated that national farm labor shortages are non-existent. A common claim within these studies is that during periods of high national unemployment, unemployed domestic workers will fill seasonal farm jobs. However, there is almost zero substitution between native born farmworkers and foreign born farmworkers (Kandel, 2008). Furthermore, industry specific farmworker shortages have been witnessed, such as the labor shortages in the dairy industry due to immigration enforcement on unauthorized workers as examined by Rosson (2012). Horner (2011) provided Congressional testimony regarding farmworker labor shortages on his Georgia blueberry farm. According to his testimony, he followed the recommended procedure aimed at hiring only authorized workers for the 67 seasonal employees required for harvest. However, he was only able to find and hire six authorized workers; four of which worked for three days or less, two of which worked for only two weeks, and no authorized workers finished the entire harvest season. 90% of Horner's 67 workers needed for the 2010 harvest season were still unauthorized and illegally working in the U.S.

A historical understanding of immigration legislation and regulation in the Southeast will help provide context for the current state of farm labor in the area. A summary of immigration regulation as it relates to farm labor in the Southeast is provided next.

History of Farm Labor, Immigration, and Harvest Mechanization in the Southeast

1942-1964, Bracero Program

The Bracero Program was a bilateral agreement between the U.S. and Mexico that created an agricultural guest-worker program in the U.S., and helped expand labor-intensive specialty crop production in Florida, Georgia, and Texas (Morgan and Gardner, 1982). The program triggered an overall increase in total farm employment, but an overall lowering of agricultural worker wages (Morgan and Gardner, 1982). Florida sugar cane farmers used the Bracero Program to secure and employee laborers from the Caribbean nations; however, the migration of Bracero era farmworkers from Central America and Mexico to the Southeast U.S. was rare (Cravey, 2003).

1964-1986, Tomato harvesters and stagflation

Increases in U.S. Department of Agriculture (USDA) funding for the development of machine harvesting technologies, coupled with the simultaneous innovations of tomato harvesters and uniformly ripening tomatoes, led to a decrease in the usage of native born or authorized immigrant labor because many of these workers would receive fewer hours and a reduction in pay (Martin, 1998). Authorized workers left the agricultural labor forces causing an increase in the usage of unauthorized workers and an increase in illegal immigration into the U.S. (Martin, 1998). Wise (1974) found that farmers rarely hired American born workers, who demanded higher wages during this period. Instead farmers would rather employ unauthorized worker for depressed wages, or just demand fewer workers, until mechanization of crop harvesting became available. Funding for farm mechanization started to decrease substantially with the stagflation problems of the late 1970s and much of the university research into agricultural mechanization and plant breeding for mechanization was shelved (Sarig, Thompson and Brown, 2000).

In the early 1970s geographers noticed an increase in Hispanic migration to areas in the South that focused on poultry processing (Winders, 2005). Researchers developed fruit, vegetable, or horticulture (FVH) crops during this period that would eventually proliferate throughout the South, such as Rabbiteye blueberries and hybrid tomatoes, but large commercial FVH operations outside of Florida were rare during this period.

1986-1996, Immigration Reform and Control Act

The Immigration Reform and Control Act (IRCA) of 1986 provided a pathway to legalization for undocumented immigrants, many of whom were farm laborers

(Department of Homeland Security, 2014; Martin, 2002). This program led to short-term decreases in the labor supply of farmworkers (most in the FVH industry were unauthorized by this time), as newly legalized farmworkers transitioned to non-farm jobs (Martin, 2002). However, Gunter, Jarrett and Duffield (1992) explained that this decrease in farmworker supply was short lived as illegal immigration continued and even accelerated, while the demand for farmworkers did not drastically change since mechanical substitution for permanent and seasonal laborers for many agricultural industries either did not exist or was inefficient. Some Southern states, such as North Carolina, extensively used the Federal H2-A immigrant agricultural work visa program (formerly H2 immigration work visa program set up under the Bracero Agreement in 1964) to supply seasonal and permanent farmworkers. This created a formal labor market of authorized agricultural farmworkers in the state, but in doing so also increased the supply of unauthorized workers who did not meet the H2-A requirements thereby decreasing labor wages. The H2-A program also divided ag-business employers into those that were willing to accept the costs of H2-A mandated housing and transportation, and those that would risk hiring unauthorized workers and did not have to pay for housing and transportation (Martin, 2012).

1996-Present, Illegal Immigration Reform and Immigrant Responsibility Act

The Illegal Immigration Reform and Immigrant Responsibility Act of 1996 was a complex bill focusing on immigration enforcement and establishing the E-Verify system for the stated purpose of reducing unauthorized employment (Department of Homeland Security, 2014). However, this legislation has not effectively decreased the supply of undocumented farm laborers, nor increased American born farm laborers in the U.S. or the Southeast. Instead, E-Verify put the burden of potential fines for hiring undocumented farm laborers on producers, leaving them increasingly financially vulnerable (Devadoss and Luckstead, 2008). By 2007, 75% of the hired farmworkers in the FVH industry were undocumented (Martin and Calvin, 2010).

During this time period it is important to note the significance of many new varieties and cultivars of specialty crops being developed at research universities, which could expand production to new growing regions of the Southeast (SHB blueberries and sweet potatoes especially). Demand for specialty crops expanded in the U.S. and abroad due to health research, marketing, and free trade agreements (Hu, Woods, and Bastin, 2009). Also, there was renewed interest in machine harvesters for many specialty crop sectors as policies like E-verify caused producers to worry about farm labor shortages which could cause wage increases, and to reevaluate their production methods (Huffman, 2012).

2002-Present, State and Local Legislation

In 2006 the Georgia Security and Immigration Compliance Act (SB 529) was signed into law creating the Southeast's strictest state-led immigration enforcement legislation. Signing Governor George "Sonny" Perdue stated the goal of the law was to decrease the number of undocumented workers within the state by making living in Georgia as an undocumented worker unappealing so that "taxpayers are not taken advantage of", although no cost analysis of undocumented immigration was conducted for the state (Winders, 2006). The SB 529 law created an unappealing environment by banning undocumented residents from receiving public housing and food assistance, limiting undocumented student's access to higher education, deputizing local law enforcement as immigration agents, and banning employers from claiming wages paid to undocumented workers as tax deductible. McKissick and Kane (2011) and Zahniser, et al. (2012) state that SB 529 decreased the ability for Georgia farmers to find farmworkers and that Georgia farmers hired fewer workers following the law's passage.

The Beason-Hammon Alabama Taxpayer and Citizen Protection Act, SB 56, was established in 2011 in Alabama as anti-illegal immigration legislation (State of Alabama, 2012) and has been economically analyzed more than other recent Southeastern immigration legislations. Its goal, similar to Georgia's SB 529, was to deter undocumented workers from showing up for established jobs and seasonal jobs, realizing that it would affect workers, and farm producers (as well as other industries). However, due to the deputizing of local law enforcement as immigration officials, many documented Hispanic workers also left the state for fear of persecution (Passel and Cohn, 2011). Thus, the effect of this bill was that both undocumented and documented laborers left the workforce in Alabama at a rate of 40,000 to 80,000 workers per year since the passage of the legislation (Addy, 2012). 13.9% of these workers that have left the Alabama workforce were in the agriculture industry (Passel and Cohn, 2011). The total economic effect of those farm workers walking away from their jobs within the agriculture industry in Alabama, specifically labor intensive specialty crops, is still being studied. However, Addy (2012) estimates the total loss in gross domestic product (GDP) for Alabama due to impacts on immigrant heavy labor sectors (such as specialty crop agriculture and construction) to be between \$2.3 and \$10.8 billion. Similar legislation is pending in many other Southeast legislatures such as Mississippi, North Carolina and Florida.

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 (Department of Homeland Security, 2014). However, no U.S. counties adopted this section until 2002. From 2002 to 2011, 69 jurisdictions then adopted 287(g) including Southeastern counties in North Carolina, Florida, Georgia, and Alabama (Kostandini, Mykerezi, and Escalante, 2014). Kostandini, Mykerezi, and Escalante (2014) report that the goal of these agreements is specifically to reduce local immigrant populations by increasing arrests for petty crimes and traffic violations in order to process immigration violations. Kostandini, Mykerezi, and Escalante (2014) go on to conclude that counties that have 287 (g) agreements experience declines in farm worker availability. In order to mitigate declining farm worker availability, farm managers increase farm worker wages in order to attract seasonal farm workers to heavily policed areas.

Summary

The Southeastern blueberry industry is currently experiencing robust growth due to increases in demand and production. Southeastern growers traditionally would use available immigrant labor for hand harvesting and look to maximize revenue for fresh market production while accepting high labor costs. Machine harvesting technology (MHT) innovations for Southern cultivars let Southeastern blueberry growers decide whether to continue hand harvesting, or adopt MHT to minimize labor costs, understanding that there would be a decrease in revenues because berry production would be for the processed market. However, recent innovations in machine harvesting technology and plant breeding have allowed Southeastern blueberry growers the opportunity to experiment with both types of harvesting methods, observing their economic benefits and costs. Concurrently, a series of national, state, and local legislations concerning immigration and enforcement have added a degree of insecurity to Southeastern blueberry grower's hand harvesting workforce. Due to the uncertain economic efficiency of new MHT and the uncertainty of labor availability, Southeastern blueberry growers are simultaneously forced to compare the costs and benefits of these two technologies, both of which have large degrees of variability. Furthermore, these technologies are vital to the production process and either decision has a significant effect on future revenue streams and production cost.

CHAPTER III

LITERATURE REVIEW

Introduction

The Literature review section is divided into three subsections. The first subsection reviews literature pertaining to the substitution of capital for labor and how that process is conducted. The second subsection reviews literature pertaining to labor, immigration, and mechanization from a national perspective. The third subsection reviews literature from previous adoption studies that are pertinent to variables used in this study.

Adoption Literature

Hicks (1932) proposed the hypothesis of induced innovation as a way to demonstrate that increases in the prices of factors of production incentivize innovations in order to decrease those specific factor costs. This hypothesis is often used in the context of factor prices for labor spurring labor saving innovations. Samuelson (1965) observes the tautology of Hick's (1932) hypothesis in a dynamic setting: a rational cost-minimizing entrepreneur will eventually choose factors of production that minimize costs. Samuelson advanced Hick's theory by postulating that it is the relative ratio of capital to labor as factors of production that induces innovation, rather than Hick's notion that labor and capital are perfect substitutes, and innovations are introduced as a way for a profit maximizing entrepreneur to minimize labor costs. Samuelson demonstrated that an entrepreneur experiences long-run equilibrium when both factors of the capital/labor ratio are increasing. Thus, as a long-term trend of increasing costs of labor exists, research into innovations that are either labor saving or labor augmenting are necessary to maintain capital/labor ratio equilibrium. He suggested that all machines are in fact invented to improve efficiency, but also that machines do not work in a vacuum and require human operators in order to be truly profit maximizing.

Kislev and Petersen (1981) hypothesized that there are two main reasons for the switch from manual labor to machine labor in agriculture. These reasons are technical changes in agriculture that are developed by agricultural researchers to render labor less efficient than machines, and manual laborers leave the agricultural sector as a market phenomenon due to wage increases in a substitute labor sector (such as construction or service), and as a result agricultural operators are forced to switch from manual labor to machinery. However, Kislev and Petersen (1981) failed to recognize a causal effect of the switch from manual labor to machine labor in agriculture: immigrant labor (which could be more economically efficient than the alternative) being coerced out of the market due to governmental policies regarding low-skill immigration and immigration status enforcement.

Marra, Pannell, and Abadi Ghadim (2003) review adoption literature concerning agricultural technology adoption and risk and uncertainty. They distinguish between adoption and diffusion theory, where adoption refers to the static process of an entrepreneur deciding to use an innovation based on profit maximizing or cost minimizing expectations. They emphasize that there is not a unifying theory on risk preferences, uncertainty, and adoption of agricultural innovations. For example, studies such as Shapiro et al. (1992) discovered that adopters of double cropping techniques were more likely to be self-described as risk averse which directly contradicts Marra and Carlson's (1990) findings that adopters of double cropping are less likely to be risk averse using an Arrow-Pratt risk formula based on perceived variability in prices and quantities. Marra, Pannell, and Abadi Ghadim (2003) contribute to adoption literature by including risk perceptions of agricultural innovations in their adoption studies; however, they fail to recognize that risk perceptions of the status quo alternative to that innovation can also be significant in determining motivations for adoption.

Straub (2009) suggests that adoption and diffusion are not just individual acts, but also have a social context based on emotional and cognitive concerns. Individuals make their adoption decisions based on the perception of the technology that they have constructed, which is molded by their communication and socioeconomic status. Thus, early adopters are often distinguished from late adopters by having access to broader amounts of information, higher socioeconomic status, higher educational attainment levels, and are less risk averse than their counterparts. However, studies such as Straub (2009) have been the subject of criticism by Doss (2006) who states that adoption studies too often focus on farm and farmer characteristics, lack awareness of policies as a causal effect of adoption, and that adoption studies do not prescribe policy changes.

Labor, Immigration, and Mechanization Literature

One of the first specialty crop machine harvesters to be developed and commercially used was for processed tomatoes. Schmitz and Seckler (1970) analyzed the adoption of machine tomato harvesters and found what they deemed "gross social returns" (being cost savings due to mechanical harvester usage per ton multiplied by total production after achieved equilibrium) exceeded that of "net social returns" (being production value using machine harvesters minus the economic consequences of unemployed laborers). This cost saving to tomato producers led to an increase from 25% of California tomatoes harvested by machines to 95% in just six years from 1965 to 1970. This adoption and diffusion process was so fast that Schmitz and Seckler (1970) worried that this type of technical displacement would lead to such large social costs in farmworker communities that large social compensation programs would be needed to stem hypothetical revolts.

Zepp (1973) measured substitution effects of labor for machine tomato harvesters after the end of the Bracero program in 1964 and the systematic increase in the national minimum wage from 1967 to 1971. Zepp (1973) estimated the variable cost for labor of hand-picked fresh market tomatoes to be less than the fixed cost of machine harvesters and variable cost of the complementary labor. Zepp (1973) observed that growers weighed the risks of higher production costs after machine harvester adoption with the risks of reduced labor availability from the end of the Braceros. This reduction in labor availability was also driven by workers leaving the tomato labor market as growers realized that they could pay a lower hourly wage for labor complementing mechanical harvesters, as opposed to the higher piecemeal[1] wages when exclusively using hand harvesting labor.

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[1] Piecemeal wages are an agreed upon wage paid to the worker determined by the amount of work completed in a time period. In FVH harvesting, piecemeal wages are often determined by the number of uniform sized bins harvested by the worker per day. Thus, a worker who harvests 27 bins of Florida tomatoes per hour would earn more than a worker harvesting 15 bins of Florida tomatoes per hour.

Napasintuwong and Emerson (2004) estimated the elasticity of substitution between labor and capital for Florida agriculture in the context of immigration policy changes. They used a Morishima Elasticity of Substitution (MES) model to demonstrate changes in price and quantity ratios on relative factor share. The MES model provides information in a cost minimization setting by setting output constant, but changing production decisions and input prices. They conclude that capital (mechanization) is a substitute for both self-employed labor and hired labor in the Florida agricultural market, particularly when the prices of labor increase due to immigration legislation. However, if capital becomes less expensive due to innovation and availability and is adopted, labor becomes a complement of capital and employment could also rise.

Martin (2007) explained how increases of border enforcement mechanisms on immigrant farm workers (arrests, detentions, and deportations) in California in 2004-2005 led to an overall decrease in labor for the winter fruit and vegetable season in California. These stops then discouraged documented farmworkers from attempting to look for seasonal farm work as they were unsure about American labor laws. This labor shortage caused industries such as raisin grapes to experiment with machine harvesters that are typically used for wine grape harvesting (and very similar to the over the row mechanical harvesters used on blueberries). However, Martin (2007) notes that the substitution of hand labor for machine labor is not easy or direct for the farmer, as packers and processors are usually organized to either sort hand-picked or machine picked fruit and vegetables, but not both. Martin (2007) noted that some farmers actually preferred

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However, employers must still adhere to Fair Labor Standards Act (FLSA) and not pay a worker less than the effective minimum wage (Roka, 2009).

machine harvesters during this period, but would not be able to switch from hand harvesting until packers and processors changed their production process.

Zahniser, Hertz, Dixon, and Rimmer (2008) used a simulation based model to look at the effects immigration legislation would have on the agricultural sector and the implications for the substitution of farm machinery for labor. They estimate that there is almost zero substitution between foreign born farmworkers (authorized or unauthorized) and native born farm workers. Thus, simulated policies that affect immigration, particularly unauthorized farm labor, would decrease the long-run agricultural output of the U.S. by 1.7-3.5 percent due to an overall loss in labor and productivity. Furthermore, agricultural sectors that rely heavily on farm labor (fruits, vegetables, and nuts) would experience larger decreases in output and exports than non-labor intensive sectors like oilseeds and grains.

Borjas (2003) used simulation based models to generate wage effects of a purely native born male workforce from 1980 to 2000. He then compared those simulated wage effects with the actual wage data using a native and immigrant (documented and undocumented) workforce over the same period. During that period, Borjas (2003) calculated an 11% increase in the labor supply of working males and estimated an own factor price elasticity between -0.3 and -0.4. Borjas (2003) distinguishes workers by their level of educational attainment and notes that employment competition between natives and immigrants exist exclusively within the parameters of these levels. Within the lowest level of educational attainment, high school dropouts, he states that the immigration influx from 1980 to 2000 decreased wages by 8.9%. Subsequent studies such as Calvin and Martin (2010) make the assumption that seasonal farmworkers, especially those in the FVH industries, are in the lowest level of educational attainment group.

Calvin and Martin (2010) use Borjas' (2003) simulations to demonstrate that historical influxes of immigrant farmworkers leads to a decrease in overall farmworker wages to the benefit of capital owners by an estimated $8 billion annually. However, due to enforcement mechanisms on workers, wages demanded have increased. This wage increase also includes the costs of worker's desires to return across the border for holidays (which is both expensive and dangerous for both legal and illegal routes) and the opportunity costs of leaving the informal economy of Mexico and Central America. Recently, enforcement mechanisms on employers such as the required use of E-Verify, raids during harvest season, and fines, have renewed an interest in mechanical harvesters. This enforcement effort seemed coordinated with a fiscal year (FY) 2009 $230 million grant to the USDA Specialty Crop Research Initiative, of which one research area was labor-reducing harvest mechanization innovations.

Calvin and Martin (2011) analyzed five different specialty crops (raisins, oranges, lettuce, strawberries, and asparagus) that are labor sensitive in the U.S. Calvin and Martin (2011) established differences in machine harvesting-labor substitution across these crops, and determined the impact that any 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, but that the responses in adoption, production, and price would vary across commodity.

Past Literature Concerning Explanatory Variables Used in Adoption Studies

Daberkow and McBride (2003) researched the adoption decisions of American farmers to precision agriculture (PA) technologies using a logistic regression model (logit) to determine farm and producer characteristics of those who adopt. This paper is highly cited for its categorizing of variables related to adoption of lumpy agricultural technologies. These categories are farm size, human capital, risk and risk preference, tenure, labor supply with regards to income, credit constraints, and location factors.

Just and Zilberman (1983) determined that the fixed expenses of lumpy agricultural technology adoption can often dissuade smaller landholders from adopting new technologies as compared to larger landholder's adoption decisions. They surmise that larger landholders often have the ability to experiment with the technology on a portion of their fields before complete adoption, in effect testing the technology, while smaller landholders feel required to use the technology on their entire operation if the technology is a large fixed expense.

Fernandez-Cornejo, Hendricks, and Mishra (2005) modeled the adoption decision process of converting to herbicide tolerant (HT) soybeans in the U.S. using a variety of human capital variables. They found significance with age, number of children in the household, farm typology, and off-farm income. Fernandez-Cornejo, Hendricks, and Mishra (2005) concluded that the probability of adoption of HT soybeans is positively explained by off-farm income, and that the elasticity of off-farm income with respect to the probability of adoption is close to +1.0.

Koundouri, Nauges, and Tzouvelekas (2006) found that the farmer's level of education is significant in modeling irrigation adoption decisions among Greek currant farmers. They correlate educational attainment to extension service visits and information access and find positive significance to the probability of adopting irrigation technologies. Koundouri, Nauges, and Tzouvelekas (2006) infer that higher educational attainment and access to extension information decreases the value of waiting to adopt a technology until another farmer has tested it.

Abadi Ghadim, Pannell, and Burton (2005) distinguish between risk perceptions and risk preferences but assert that both are significant factors in explaining adoption decisions, according to their study on chickpea adoption in Australia. They found that risk-averse farmers tended away from adoption of a complementing chickpea crop. They also suggested farmers believed that the risk associated with chickpea adoption is greater than the benefits of crop diversification, thus the perception of the risks associated with chickpea adoption are significant.

Feder (1980) asserts credit constraints are also an important explanatory variable in the adoption decision process. He states that the larger the credit constraint associated with either the technology being adopted or the factors of production, the more risk averse the farmer becomes decreasing the probability of adoption. Conversely, the presence of credit availability increases the probability of adoption by the farmer, as well as investing in a larger farm in which Just and Zilberman (1983) show also increases the likelihood of adoption.

Pham and Van (2010) develop a theoretical model for how immigration enforcement legislation affects wage variation in jobs with a high proportion of immigrant labor, including farm worker labor. However, they note the difficulties of determining whether the wage variation is caused by the supply curve or the demand curve. If enforcement legislation causes fewer immigrant laborers to enter the labor market, the supply curve shifts right decreasing quantity of laborers and increasing the price of labor. However, because enforcement programs such as E-verify of the 1996 IIRARA burden employers who knowingly hire undocumented workers, demand for immigrant laborers is less rewarding, and the demand curve is either shifted to the right decreasing the price of labor, or rotating the demand curve. Either effect confirms that the wage variability can be used as a measure of labor uncertainty in farm labor markets, as exemplified by Kostandini, Mykerezi, and Escalante (2014).

Summary

Agricultural innovation adoption literature has shown that substitution between labor and capital, especially labor saving harvesting technology, is a process that involves three distinct components. The first causal component of agricultural technology adoption involves understanding the risks associated with the innovation and the status quo. Being able to quantify risk perceptions associated with the alternatives, as well as quantify risk preferences of the producers, will develop insight into the adoption process. Literature has also demonstrated that a contextual understanding of immigration policy, as immigrants make up an expanding portion of the agricultural workforce, is necessary to understand motivations for agricultural technology adoption. Furthermore, literature has demonstrated that immigration policies have an effect on both the supply and demand of agricultural workers which in turn affects farmworker labor prices, and induces the consideration of substitution for labor saving agricultural technologies. Lastly, adoption literature has established the need to quantify farm and farmer characteristics when estimating motivations for technology adoption. It is important to note that FVH farms in the U.S. are not as homogenous as commodity crops, and the decision for technology adoption may lie more with personal characteristics than the need to maintain the technology treadmill effect as described by Cochrane (1993)[2].

[2] Cochrane treadmill refers to the process by which a small group of farmers adopt a new technology that lowers their production costs and increases their profits in the short run. Soon, all farmers adopt the technology increasing production without increasing demand causing profits to decline. Thus, adopting a newer technology is now the only manner in which to reestablish increasing profits.

CHAPTER IV

METHODOLOGY

Introduction

Adoption literature provides a foundation for a theoretical framework and empirical methods. The first subsection of this chapter concerns theory associated with labor saving technology adoption studies. The second subsection concerns the empirical model for the logistic regression. The third subsection is a description of the data used in the empirical model.

Theoretical Framework

Determining the probabilistic individual choice of adopting a mechanical blueberry harvester is one of the underlying goals of this study. Modeling human choice behavior is complex because the econometrician cannot directly measure all the factors that make up individual utility. However, we can deduce probabilities of individual choice from the choice behavior of the study population, especially because the decision maker's alternatives in this study are discrete: mechanical blueberry harvester technology versus manual harvesting technology. We can also assume that the decision maker is making their consumer choice, in this case what type of labor technology to consume, because the selected alternative maximizes their individual utility. McFadden (1974) provides a framework for choice behavior stating they must include the choice and a set of alternatives, attributes of the decision makers, a model of choice and behavior, and a distribution of behavior patterns associated with the choice and alternatives.

McFadden (1974) outlines how observed data of a population can then be qualitatively analyzed to determine probabilities of individual choice. We let an individual drawn from the observed population have a probability of choosing alternative *j* as $P(j|s,\boldsymbol{B})$, where *s* is the set of measured attributes of the individual and $\boldsymbol{B}$ is the set of available alternatives that includes alternative *j*. Individuals are assumed to use behavior rules, noted by function h, which for example may include a demand function as a product of profit maximization, cost minimization, or risk minimization (this will be further developed in the following section). Model $\boldsymbol{H}$ is a set of individual behavior functions *h*, where $\boldsymbol{H}$ can contain multiple behavioral rules across the population. There then exists a probability π, defined on the subsets of $\boldsymbol{H}$ and assumed to be a member of a parametric family, which specifies the distribution of the behavior rules in the population. Thus, the probability of choosing the alternative *j* is equal to the probability of the incidence of behavioral rules causing a choice decision yielding alternative *j*:

$$P(j|s,\boldsymbol{B}) = \pi[\{h \in \boldsymbol{H}|h(s,\boldsymbol{B}) = j\}]. \tag{4.1}$$

Equation (1) lets us build an econometric model of choice behavior of a utility-maximizing economic consumer using a random utility function. Random utility functions let us predict the probability of a choice set without directly measuring utility. Individual *i's* random utility function can be modeled as:

$$u_{ij} = v_{ij} + \varepsilon_{ij}, \tag{4.2}$$

where v_{ij} is the deterministic component based on measurable attributes of the individual *i* and attributes of alternative *j*, and ε_{ij} is the stochastic error component of unobserved attributes of the individual *i* and alternative *j*. Alternative *j* is described by the vector of attributes $\boldsymbol{x}_j$. Thus, the probability that an individual *i* from the study population will choose alternative *j* is:

$$\begin{aligned} P_i(\boldsymbol{x}_j|s,\boldsymbol{B}) &= \pi[\{h_i \in \boldsymbol{H}|h_i(s,\boldsymbol{B}) = \boldsymbol{x}_j\}] \\ &= P_i[v_{ij} + \varepsilon_{ij} > v_{ij'} + \varepsilon_{ij'}], for\ all\ j \neq j'. \end{aligned} \tag{4.3}$$

This specification can then be deconstructed into a joint distribution function in order to generate probabilities of choosing an alternative based on the unknown parameters of the distribution. Furthermore, we assume error terms to be independently and identically distributed following a Gumble (type 1 extreme value) distribution. This assumption yields a logit model:

$$P_i(Y = 1|\boldsymbol{x}_j) = \frac{e^{x_{ij}\boldsymbol{\beta}}}{1+e^{x_{ij}\boldsymbol{\beta}}} = \Lambda(\boldsymbol{x}_{ij}\boldsymbol{\beta}) \tag{4.4}$$

where *Y* is discrete random variable (Greene, 2002). Maximum likelihood is the estimation technique for logit models. Logit models, including binary and multinomial logit models have been broadly used to investigate characteristics correlated with agricultural technology adoption behavior. Studies such as Daberkow and McBride (2003) use similar logit techniques to describe the adoption of precision agriculture technologies.

Estimated coefficients are not directly interpretable, thus marginal effects must be calculated in order to determine unit change effects of continuous variables. Marginal effects for continuous independent variables are calculated as the mean of the marginal effect for each observation with the latter calculated using:

$$\frac{\partial E(Y|\boldsymbol{x}_{ij})}{\partial \boldsymbol{x}_{ij}} = \Lambda(\boldsymbol{x}_{ij}\boldsymbol{\beta})[1 - \Lambda(\boldsymbol{x}_{ij}\boldsymbol{\beta})]\boldsymbol{\beta}. \tag{4.5}$$

Marginal effects for discrete explanatory variables are calculated using:

$$\frac{\partial E(Y|\boldsymbol{x}_{ij})}{\partial \boldsymbol{x}_{ij}} = \Pr[Y = 1|\boldsymbol{x}_{ij(d)}, d = 1] - \Pr[Y = 1|\boldsymbol{x}_{ij(d)}, d = 0], \tag{4.6}$$

where d is the discrete variable and the marginal effect is calculated at d=1 and d=0 for each observation. The two series of marginal effects are then averaged and the difference between the averages are reported (Greene, 2002). Marginal effects for variables that have a quadratic term were calculated using:

$$\frac{\partial E(Y|\boldsymbol{x}_{ij})}{\partial \boldsymbol{x}_{ij}} = \left(\frac{e^{x_{ij}\beta}}{\left(1+e^{x_{ij}\beta}\right)^2}\right)(\beta_l + 2\beta_q x_{ij}), \tag{4.7}$$

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 inflection point (the point where the change in probability reverses sign) for explanatory variables with a quadratic term is calculated using:

$$\frac{-\beta_l}{2\beta_q}. \tag{4.8}$$

Marginal effects are directly interpretable as a unit change in the independent variable causing a probability change in the dependent variable.

Empirical Model of Machine Harvester Technology Adoption

The specification of the empirical logit model to analyze machine harvester technology among Southeast blueberry growers uses variables from previous literature on agricultural technology adoption and variables specific to the Southeastern blueberry market and agronomy. These explanatory variables can be divided into categories similar to Daberkow and McBride's (2003) precision agriculture adoption study variable categories, such as human capital, risk, credit constraints, tenure, production, and agronomic constraints. Our human capital variables include age and experience of the grower, risk preference variables include a stated willingness to accept risk compared to peers and observed crop insurance purchases, tenure variables including experience and ownership transfer intentions, production variables include acreage and yield data, and agronomic variables include age, cultivar, and location.

Nearly all respondents were white and male, thus race and sex were not valuable explanatory socioeconomic variables. Variables related to credit constraints and financed property (Daberkow and McBride, 2003; Feder, 1980) were not significant. Responses to percentage of income gained from off-farm activities (Fernandez-Cornejo, Hendricks, and Mishra, 2005) were generally omitted resulting in missing data, and including the variable would dramatically decrease usable observations. According the Godfrey (1990) both level of educational attainment (Koundouri, Nauges, and Tzouvelekas, 2006) and years of experience act as a proxy for management abilities and learning, and are often correlated leading to model misspecification. Thus, only experience variables were used in the model due to the high amount of omitted level of educational attainment responses. 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). Variables measuring size of household (Fernandez-Cornejo, Hendricks, and Mishra, 2005) were not significant. However, plans to transfer ownership to a family member were included in the model to capture similar human capital explanatory variables.

The standard deviation of wage variable was added to determine if wage variation, as a product of immigration legislation and enforcement, explains harvester adoption (Kostandini, Mykerezi, and Escalante, 2014). Average county wage rates for the 36 quarters from 2001 to 2009 did not show annual wage variation and wages for a single year would not explain those that adopted MHT much earlier than 2010. The inclusion of average wage and a single year wage variables with the standard deviation of wage variable were highly correlated and led to misspecification. Discrete variables for Georgia and Florida farms were added to determine if regional differences exist in adoption patterns. Variables for Mississippi and North Carolina were insignificant or lead to model misspecification, possibly due to low number of observations.

The empirical discrete logit model used to analyze machine harvester technology adoption among Southeast blueberry growers was specified as:

$$MACHINE_i(y=1) = \beta_1 YEARS_i + \beta_2 YEARSSQ_i + \beta_3 AGE_i + \beta_4 AGESQ_i + \beta_5 PROD_i + \beta_6 PROD_i * RBBT_i + \beta_7 PROD_i * BOTH_i + \beta_8 CROPINS2_i + \beta_9 CROPINS4_i + \beta_{10} WTARISK2_i + \beta_{11} WTARISK3_i + \beta_{12} WTARISK4_i + \beta_{13} TRANFEROWN_i + \beta_{14} WAGESTD_i + \beta_{15} WAGESTD_i * RBBT_i + \beta_{16} WAGESTD_i * BOTH_i + \beta_{17} FL_i + \beta_{18} GA_i + \varepsilon_i, \tag{4.9}$$

where the variables are defined in table 4.1 and i identifies the i^{th} response. β_1 through β_{18} are the parameters to be estimated. Due to the agronomic differences between Rabbiteye and Southern Highbush cultivars, interactions with the explanatory variables were considered, and pretesting concluded that the interactions were significant with production variables and the standard deviation of wage variables. Table 4.1 presents the descriptions of the variables used in equation (4.9).

Table 4.1 Definitions of Variables Used in the Discrete Logit Analysis of Machine Harvester Adoption among Southeastern Blueberry Growers

Variable Name	**Description**
MACHINE	1 if farmer used a mechanical harvester for all or part of 2010 harvest, 0 otherwise
YEARS	Number of years of experience blueberry farming
YEARSQ	YEARS variable squared
AGE	Farmer's age
AGESQ	AGE variable squared
PROD	Number of acres of blueberries multiplied by 2010 average yield in 1,000 lbs. Southern Highbush growers only by default
RBBT	1 if Rabbiteye growers only, 0 otherwise
BOTH	1 if both cultivar growers, 0 otherwise
CROPINS2	1 if 1-6 crop insurance purchases from 2001 to 2010, 0 otherwise.
CROPINS4	1 if 7-10 crop insurance purchases from 2001 to 2010, 0 otherwise.
WTARISK2	1 if respondent answered 2 on a Likert scale of willingness to accept risk as compared to peers, 0 otherwise. We defined this level of risk as intermediate
WTARISK3	1 if respondent answered 3 on a Likert scale of willingness to accept risk as compared to peers, 0 otherwise. We defined this level of risk as increased
WTARISK4	1 if respondent answered 4 on a Likert scale of willingness to accept risk as compared to peers, 0 otherwise. We defined this level of risk as much more increased
TRANSFEROWN	1 if plan to transfer ownership to family member or associate, 0 otherwise
WAGESTD	Standard deviation of county level wages, 2001-2009, agricultural and natural resources sector, Southern Highbush growers only by default
FL	1 if respondent's farm is in Florida, 0 otherwise
GA	1 if respondent's farm is in Georgia, 0 otherwise

More years of experience (*YEARS*), as a proxy for effective management capabilities and learning, is generally expected to increase the probability of technology adoption. However, an increased age (*AGE*) of the farm manager is expected to decrease the probability of adoption. A younger farm manager is hypothesized to have more education and thus be more willing to adopt technologies according to Daberkow and McBride (2003). The squared experience *(YEARSQ)* is included to allow for the presence of a non-linear relationship between learning and adoption. Thus, more years of experience is expected to increase the probability of technology adoption, but at a decreasing rate as to allow for the expectation that an increased age of the farm manager will decrease the adoption probability. Similarly, the squared age is included to allow for a non-linear relationship between adoption and age.

Plans of transferring ownership to a family member or friend (*TRANSFEROWN*) could extend the working life of both the orchard and the technology. Thus, plans to transfer ownership to family or friends are expected to increase the likelihood of technology adoption.

Farm production (*PROD*) is included as a measure of farm size. Most mechanical blueberry harvesters have a parameter of maximum acreage the farmer can assume to efficiently harvest with one machine. However, neither harvester manufacturers nor trade journals give a minimum acreage for machine harvesting. If a farm manager elects to mechanically harvest a one acre orchard, they may do so and be within manufacturers recommended parameters for usage. The survey asked the respondent whether they used a mechanical harvester for any part of their 2010 harvest, not if they own a mechanical harvester in 2010. This verbiage allows for the possibility that a smaller producer, or group of small producers, may borrow or lease a mechanical harvester for some portion of their 2010 harvest, in the same way that small producers may share a packing facility. Therefore, small farms were included in the analysis as part of the production (*PROD*) variable.

Increases in production (*PROD*) are expected to increase the probability of mechanical harvesting technology adoption. Furthermore, low production should decrease lumpy technology adoption until these producers have complete information about the new technology, or their production is large enough to justify experimenting with a harvester on all or a portion of their crop (Just and Zilberman, 1983). The production variable (*PROD*) was interacted with a dummy variable for Rabbiteye production only (*PROD*RBBT*) and production of both cultivars (*PROD*BOTH*). These interaction terms allow us to determine if specific cultivar production influences technology adoption with varying probabilities. Because Rabbiteye has a firmer flesh and fruit, we expect the adoption likelihood to increase more with the Rabbiteye production only (*PROD*RBBT)* and the production of both cultivars (*PROD*BOTH*) than the production of Southern Highbush cultivars only.

Our model includes two distinct risk variables. The frequency of crop insurance purchases in the last ten years (*CROPINS*) is a measure of observable risk preferences. Joint tests on crop insurance purchases confirm that regions do not correspond with the number of purchases. Willingness to take on risk as compared to peers (*WTARISK*) is a measure of subjective risk preferences. Higher frequencies of crop insurance purchases by the farmer are assumed to correlate to a higher degree of risk aversion, especially as blueberry budding is highly susceptible to frost damage and severe yield reductions.

Agriculture literature generally agrees that adopting lumpy technological innovations is perceived to be more risky than continuing traditional practices (Abadi Ghadim, Pannell, and Burton, 2005). Therefore, a farmer who has stated that he frequently purchases crop insurance is assumed risk averse, and reluctant to adopt technological innovations. Accordingly, we expect frequent purchases of crop insurance to decrease the likelihood of mechanical harvester adoption. Using Abadi Ghadim, Pannell, and Burton's (2005) reasoning, increased stated willingness to take on risk compared to peers (*WTARISK*) should increase the probability of mechanical harvester adoption. A frequency test was conducted on the two risk variables and is presented in table 4.2.

Table 4.2 Frequencies of Observations of Willingness to Accept Risk (*WTARISK*) and Number of Crop Insurance Purchases (*CROPINS*)

		CROPINS		
		No purchases	1-6 purchases	7-10 purchases
WTARISK	1 (less willing)	18	14	9
	2	37	22	13
	3	38	25	10
	4 (more willing)	20	10	7

A Pearson correlation value of -0.0099 and Spearman correlation value of -0.0233 demonstrate low instances of correlation between the willingness to accept risk (*WTARISK*) and number of crop insurance purchases (*CROPINS*) variables, thus both the stated and observed risk preference observations are used in the model without misspecification.

The standard deviation of quarterly wages from a nine year period (*WAGESTD*) reveals wage variation, as opposed to wages at a single event period. This wage variation improves the ex-ante and ex-post approach to our adoption models by using wage trends, as opposed to assuming a wage at a single point in time has better explanatory power in a cross-sectional study. The standard deviation for quarterly county wage rates for agricultural and natural resource employment from 2001 to 2009 (*WAGESTD*) is used as a measure of uncertainty in the agricultural laborer sector. One reason for increased uncertainty in the labor market may be related to changes in county or state level immigration enforcement. More immigration enforcement causes more uncertainty in the agricultural labor market, causing increases in the standard deviation of wages (Kostandini, Mykerezi, and Escalante, 2014). Therefore, increases in the standard deviations of wages are expected to increase the likelihood of mechanical harvester adoption, as MHT is a substitute for a large portion of blueberry harvest laborers. These standard deviations of wages have been interacted with dummy variables for Rabbiteye only growers (*WAGESTD*RBBT*) and growers who grow both cultivars (*WAGESTD*BOTH*) in order to determine if growers of a particular cultivar are more susceptible to labor uncertainty. Increases in the standard deviation of wages for Rabbiteye growers only (*WAGESTD*RBBT*) is expected to increase the likelihood of mechanical harvester adoption at a faster rate than the likelihood of MHT adoption for growers of both cultivars (*WAGESTD*BOTH*) or Southern Highbush (*WAGESTD*) only growers due to the hardier traits of Rabbiteye berries. These berry traits have historically allowed for more mechanical harvesting than other Southeastern cultivars which, leads to lower hand-harvesting labor usage.

Between 2001 and 2010 Georgia had the strictest immigration laws of the four states surveyed. Due to increased immigration enforcement's effect on increasing agricultural wages, Georgia blueberry farms (*GA*) are expected to have a higher likelihood of MHT adoption than other states in our survey induced by labor unavailability and increased harvest wages. Florida blueberry farms receive the highest farm gate price for fresh market product as their early harvest season has zero domestic competition. Because fresh market blueberries produce a higher profit margin at this time than processed blueberries, we expect Florida farmers (*FL*) to have a decreased likelihood of MHT adoption as fresh market machine harvesters are still being studied for efficiency.

Many technology adoption surveys are conducted over time to determine both adoption likelihood and diffusion of the technology (Sunding and Zilberman, 2000). Our cross sectional survey was conducted over the course of one year thus we could not observe adoption timing or diffusion. The dependent variable for the adoption model was captured by a survey question asking if any part of the blueberry orchard had been machine harvested in 2010 therefore we are able to observe use of the technology, but not adoption timing. As a way to address adoption timing we followed up "no" responses related to use of the technology by asking whether the respondent considers using a mechanical harvester in the next five years. Responses were assessed on a Likert scale from very unlikely to very likely. Due to the low number of responses we collapsed the five-category responses into a two-category response by combining four categories from "unlikely" to "very likely" into one single category. The other category represents the "very unlikely" responses: current non-adopters who have no intention of future machine usage understanding five years of potential wage variation and harvester innovations. Model goodness-of-fit measures were used to determine this specification for the dependent variable. A binary logit model is used to analyze future indications of machine harvester usage among non-users in the next five years. We used the same independent variables[3] as the adoption model in (9). The specified model is:

$$CONSIDER_i(y = 1) = \gamma_1 YEARS_i + \gamma_2 YEARSSQ_i + \gamma_3 AGE_i + \gamma_4 AGESQ_i + \gamma_5 PROD_i + \gamma_6 PROD_i * RBBT_i + \gamma_7 PROD_i * BOTH_i + \gamma_8 CROPINS2_i + \gamma_9 CROPINS4_i + \gamma_{10} WTARISK2_i + \gamma_{11} WTARISK4_i + \gamma_{12} TRANFEROWN_i + \gamma_{13} WAGESTD_i + \gamma_{14} WAGESTD_i * RBBT_i + \gamma_{15} WAGESTD_i * BOTH_i + \beta_{16} FL_i + \beta_{17} GA_i + \eta_i, \tag{4.10}$$

where the independent variables are defined in table 4.1 and i identifies the i^{th} response. γ_1 through γ_{15} are the parameters to be estimated using the logit regression.

The ex-post consideration model (4.10) will provide parameter estimates to a stated preference towards MHT adoption, as opposed to the estimates of the observed preference of the adoption model (4.9). Thus, the directional relation of the parameter estimates of the consideration model will provide both insight into future MHT adoption, and will provide a robustness check for results of the original adoption model. By having both an ex-ante adoption model that captures how the explanatory variables explain MHT adoption likelihood to the event in 2010, and an ex-post consideration model that captures how the explanatory variables explain future MHT adoption after the event, we hope to add robustness to our variables and potentially add to adoption methodology.

[3] Willingness to accept risk discrete variable (*WTARISK3*) was combined with (*WTARISK2*) due to low number of observations

Data used in Empirical Model

Data for this study was collected from a 2011 Blueberry Industry Survey provided in Appendix A. It was distributed to members of blueberry grower associations in Florida, Georgia, North Carolina and Mississippi, states which represent the majority of blueberry production in the Southeast. Interviews were conducted with selected growers in order to determine relevant questions for their survey in the summer of 2010. Mail survey was chosen, as answers in mail surveys tend to be the least biased according to Salant and Dillman (1994). The survey method proposed by Salant and Dillman (1994) was followed, in which announcement letters are sent, 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.

The first round of mailings of announcements and questionnaires were distributed to 692 Southeastern blueberry growers in four states from February 22, 2011 to March 1, 2011. A mailing of reminder postcards were sent on March 17 and 18, 2011. Surveys to non-respondents were resent between March 21 and 24, 2011. Of the 692 surveys mailed in 2011, 234 responded for a response rate of 33.8 percent. The 2007 Census of Agriculture calculated 2,145 Blueberry Farms in the Florida, Georgia, North Carolina and Mississippi, thus the 234 respondents to the Blueberry Industry Survey represent 10.9% of blueberry farms in these select states. Additionally, the 2007 Census of Agriculture estimated 20,792 acres of tame blueberries within the four selected states. The 234 survey responses aggregate to a blueberry acreage of 12,386 acres, which represents 59.6% of total blueberry acreage in the four surveyed states, thus our survey data is more oriented towards larger commercial farms than small farms or hobby farms (USDA, Berries: 2007 and 2002). 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-ERS, 2013). Table 4.3 shows ERS data on average lbs./acre for the four states compared to average lbs./acre from our survey data for 2010.

Table 4.3 ERS average yield/acre versus survey average yield/acre for 2010

	ERS	**Survey**
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

Note: standard deviations are in parenthesis

Table 4.3 illustrates the average yield/acre data from our survey is within one standard deviation of the average yield/acre from ERS for the four states, and that our four state average yield data is within a half ton per acre of the ERS data. This average yield data, as well as the acreage data, form a representative production variable to production of larger data sets.

The survey contained 32 questions pertaining to economic conditions, farmer characteristics, production, preferences and perceptions, and social characteristics of their enterprise. The central focus of the survey was to determine usage of risk mitigating technologies among blueberry farmers for environmental, agronomic, and social risks. Of the 234 responses, 202 were suitable for use in our empirical model and summary statistics are defined in table 4.4.

Table 4.4 Summary Statistics of Variables Used in the Discrete Logit Analysis of Machine Harvester Adoption among Southeastern Blueberry Growers

Variable Name	Mean	Standard Deviation	Minimum	Maximum
MACHINE	0.36	0.48	0	1
YEARS	11.187	11.17	0	75
AGE	54.99	9.01	21	65
PROD	282.15	715.98	0	4814.5
PROD*RBBT	74.13	98.56	1	450.05
PROD*BOTH	699.24	1192.06	5	4814.5
CROPINS2	0.33	0.47	0	1
CROPINS4	0.15	0.36	0	1
WTARISK2	0.31	0.46	0	1
WTARISK3	0.31	0.46	0	1
WTARISK4	0.18	0.38	0	1
TRANSFEROWN	0.39	0.92	-1	1
WAGESTD	84.16	32.06	32.316	182.82
WAGESTD*RBBT	103.09	36.20	43.22	163.55
WAGESTD*BOTH	81.20	31.91	32.31	163.55
FL	0.35	0.48	0	1
GA	0.34	0.47	0	1

Wage data was acquired from The Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW). The wage data represents county level quarterly wages based on the North American Industry Classification System (NAICS). This study used NAICS 1011, the Natural Resources and Mining industry which includes the agriculture industry subset, being the only county level quarterly wage data available[4] (U.S. Bureau of Labor Statistics, 2013). Wage data in the QCEW is derived from summaries of employer self-reporting of wages based on state and federal unemployment insurance. Employers in the agriculture industry do not unilaterally pay federal unemployment insurance under the Federal Unemployment Tax Act (FUTA). Agricultural employers are only required to pay federal unemployment insurance (thus being recognized in the QCEW) if total wages to employees is $20,000 and over in any calendar quarter, or the employer employs 10 or more workers, full or part-time, for 20 consecutive or non-consecutive weeks within a calendar year (U.S. Department of Labor, 2013). QCEW also collects wage data from employers who pay into state unemployment systems. Georgia, North Carolina, and Mississippi have the same unemployment insurance requirements as the FUTA for agricultural employers. Florida has more stringent requirements of paying federal unemployment insurance taxes if total wages to employees are $10,000 and over in any calendar quarter, or the employer employing 5 or more workers for 20 weeks. (U.S. Department of Labor, 2010)

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[4] The National Agricultural Worker Survey also collects wage data from agricultural workers, however this data is collected annually and due to workers being interviewed in person, the sample size is small. The 2009 survey for the Southeastern region (which includes Florida, Georgia, and Mississippi) interviewed 392 farm workers, a smaller population than the number of seasonal laborers used on a single blueberry farm in our survey.

This study used average weekly wages data from the QCEW which is “pay before deductions for Social Security, unemployment insurance, group insurance, withholding tax, salary reduction plans, bonds and union dues. The figure includes pay for overtime, shift premiums, holidays, vacations and sick leave paid directly by the employer to the employee” (U.S. Bureau of Labor Statistics, 2013). This data was collected from all four calendar quarters from 2001 to 2009.

CHAPTER V

RESULTS

Table 5.1 presents results of the logit model of machine harvester technology (MHT) adoption among Southeastern blueberry growers conducted using SAS, version 9.3 software. The likelihood ratio and Wald Chi-square tests measure the goodness of fit of the model. Other measures of goodness of fit indicate a good fit with Cox and Snell R^2 values of 0.6132 for less than a [0,1] interval and rescaled to a [0,1] interval of 0.8403[5]. Values of Akaike's Information Criterion (AIC), Schwartz Criterion (SC), and -2Log L value of 264.301 establish a better model fit for the covariates than alternative model formulations.

[5] The Cox and Snell R^2 tests the global null hypothesis that beta=0, however, the dependent variable is discrete so it's upper bound must be less than 1 possibly biasing goodness of fit statistics. Max rescaled R^2 divides the original R^2 by its upper bound in order to determine goodness of fit with discrete dependent variables (Allison, 2012).

Table 5.1 Binomial Logit Model of MHT Adoption among SE blueberry Farmers Results

Variable	Description	Coefficient	Std. Error
INTERCEPT	-	-38.318***	19.213
YEARS	Year of Experience	0.176***	0.080
YEARSQ	-	-0.005***	0.002
AGE	Age of Farmer	1.157**	0.704
AGESQ	-	-0.010**	0.006
PROD	Southern Highbush production only (by default)	0.001	0.002
PROD*RBBT	Rabbiteye production only	0.017**	0.009
PROD*BOTH	Both cultivar production	0.031***	0.016
CROPINS2	1-6 purchases in last 10 years	1.128*	0.802
CROPINS4	7-10 purchases in last 10 years	6.297***	2.767
WTARISK2	Low WTA risk compared to peers	0.916	0.988
WTARISK3	Medium WTA risk compared to peers	0.398	1.007
WTARISK4	High WTA risk compared to peers	1.471	1.361
TRANSFEROWN	Plan to transfer ownership to associate	-0.214	0.373
WAGESTD	Southern Highbush farms, St. Dev. of wage (by default)	0.022	0.015
WAGESTD*RBBT	Rabbiteye farms, St. Dev. of wage	-0.009*	0.018
WAGESTD*BOTH	Farms with both cultivars, St. Dev. of wage	0.026**	0.014
FL	Florida farms	-5.135**	2.716
GA	Georgia farms	3.112***	1.199
Number of Observations	202		
Percent Concordant	97.56		

Note: *, **, *** denotes statistical significance at the 15%, 10% and 5% levels, respectively. Standard errors are conventionally calculated using a Taylor series approximation

Figure 5.1 shows the ROC Curve for the ex-ante adoption model which displays the goodness of fit using concordant pairs of predicted pairs versus actual pairs. The curve shows that 97.56 percent of the actual pairs were accurately predicted.

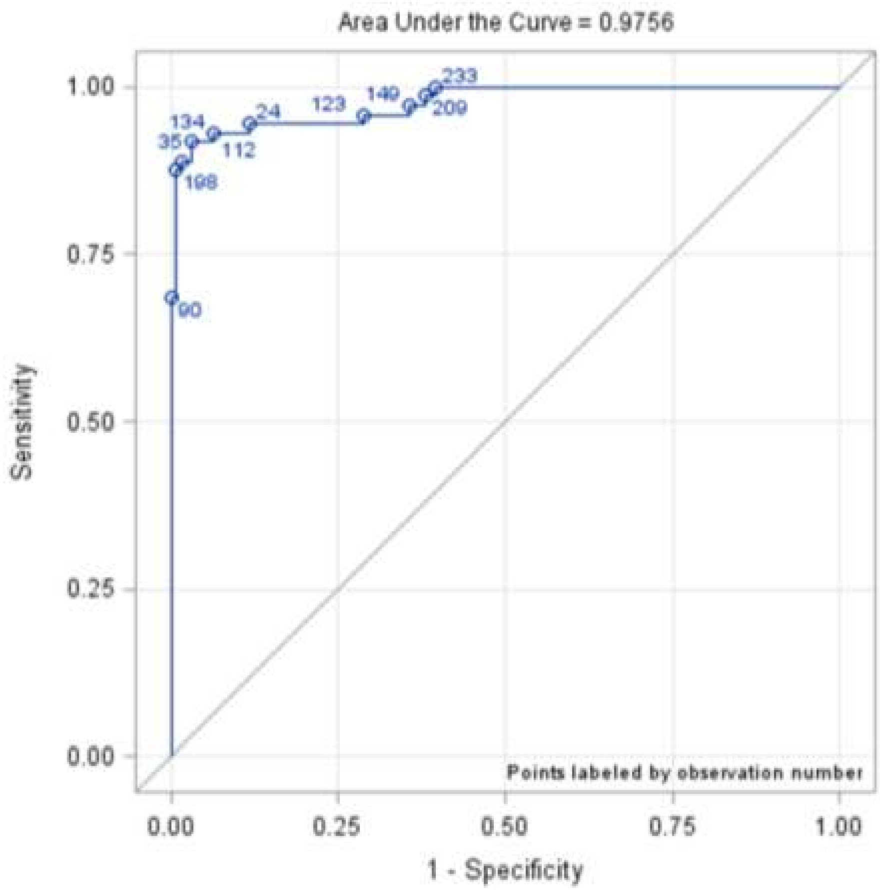

Figure 5.1 ROC Curve for Ex-Post Adoption Model

As noted in Chapter VI, coefficients of independent variables are not directly interpretable however the sign of the coefficients can be interpreted. The positive sign of the coefficient of the variable (*YEARS*) shows increases in years of experience farming blueberries increase the likelihood of having adopted MHT and is evidenced in figure

5.2. However, the negative sign of the coefficient for the variable (*YEARSQ*) reveals that while years of experience do increase MHT adoption, the rate of adoption decreases as the farmer reaches a certain amount of years of experience. The inflection point calculated for years of experience using the parameter estimates of (*YEARS*) and (*YEARSQ*) in equation (8) is 19.1 years.

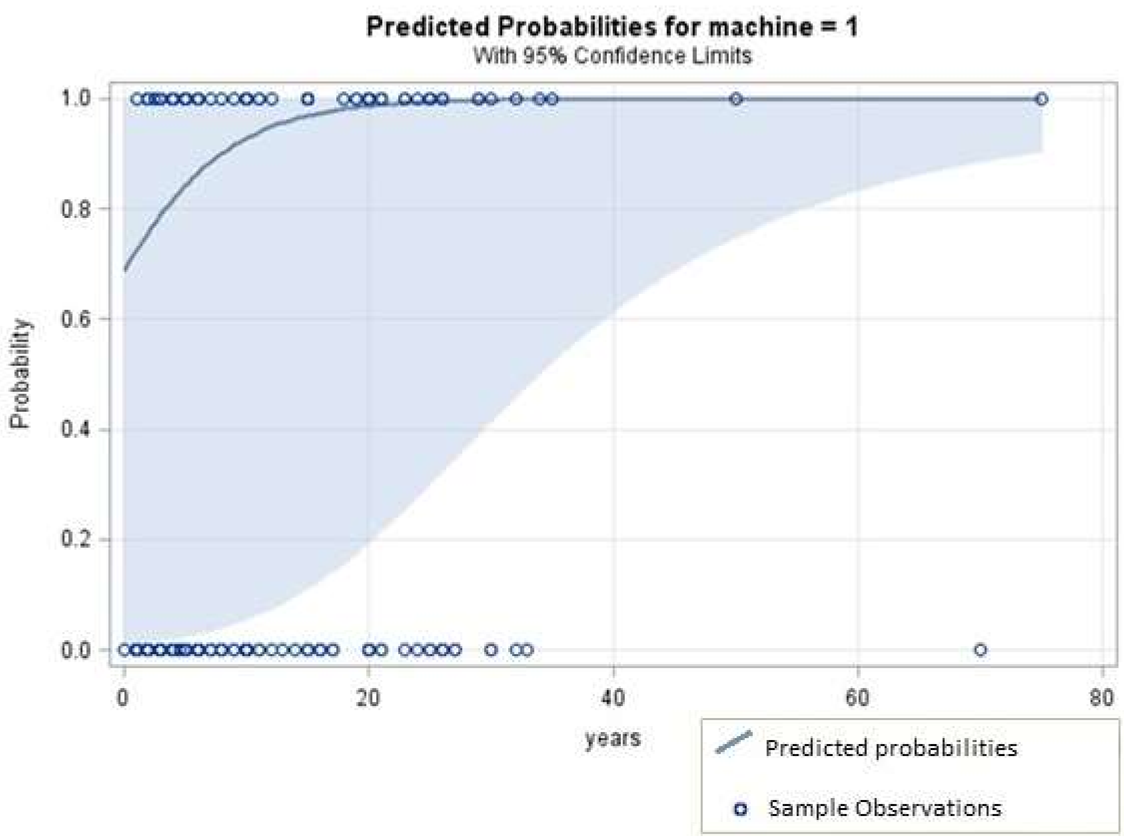

Figure 5.2 Effect Plots of (*YEARS*) on MHT Adoption

Similar to years of experience, the positive sign of the coefficient for the variable (*AGE*) shows the increases in the age of the farmer increase the likelihood of having adopted MHT evidenced in figure 5.3, however the negative sign of the coefficient for the variable (*AGESQ*) reveals age increases MHT adoption, but at a decreasing rate. The inflection point calculated for age using the parameter estimates of (*AGE*) and (*AGESQ*) in equation (8) is 56 years.

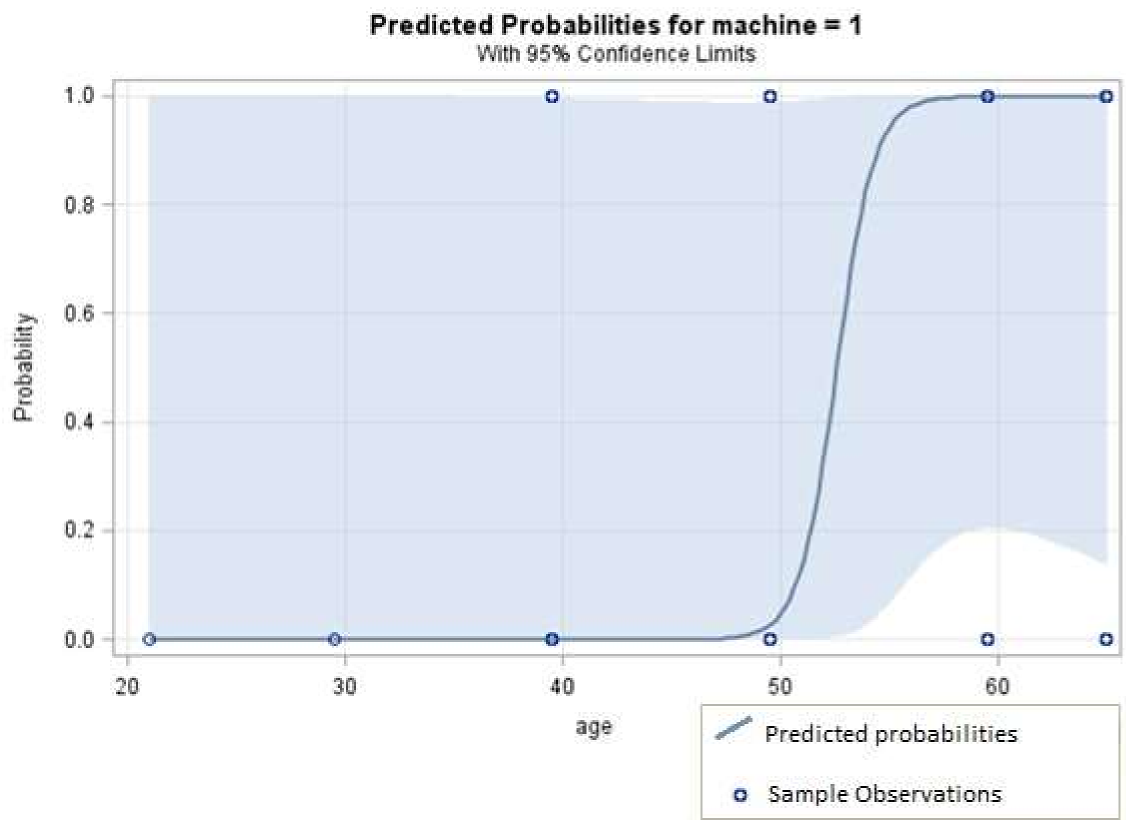

Figure 5.3 Effect Plots of (*AGE*) on MHT Adoption

Increases in production, which accounts for yield and acreage, increase the likelihood of MHT adoption. However, the magnitudes of the coefficients for production of Rabbiteye only and production of both cultivars only are much larger than the magnitude of the coefficient for Highbush production only. Thus, adoption rates increase with production increases but this rate is higher for Rabbiteye only producers and highest for diversified producers.

Farmers who frequently make crop insurance purchases, an observed measurement of risk preference, have an increased likelihood of MHT adoption. However, all variables associated with increasing willingness to accept risk as compared to peers, a stated measure of risk preference, are insignificant and their magnitudes do not demonstrate a directional effect on the probability of adoption. Increases in the standard deviation of wages, as a proxy for labor uncertainty, increase the likelihood of MHT adoption among Rabbiteye farmers and farmers of both cultivars. On the other hand, increases of the standard deviation of wages decreases the likelihood of MHT adoption among farmers who only grow Southern Highbush.

Table 5.2 presents results of the marginal effects of the independent variables on the discrete dependent variable: MHT adoption. Note that marginal effects of continuous variables are directly interpretable as a one unit change in the independent variable causes a proportional change, based on the value of the marginal effect, in the dependent variable. For dummied independent variables the marginal effect is the change in the probability of adoption when the dummy equals one.

Table 5.2 Marginal Effects of Variables in the MHT Adoption Logit Model

Variable	Method	Marginal Effect
YEARS	Calculated using equation (4.7)	0.0039
AGE	Calculated using equation (4.7)	0.0007
PROD	Calculated using equation (4.5)	0.0001
PROD*RBBT	Calculated using equation (4.5)	0.0010
PROD*BOTH	Calculated using equation (4.5)	0.0015
CROPINS2	Calculated using equation (4.6)	0.0678
CROPINS4	Calculated using equation (4.6)	0.3183
WTARISK2	Calculated using equation (4.6)	0.0526
WTARISK3	Calculated using equation (4.6)	0.0223
WTARISK4	Calculated using equation (4.6)	0.0856
TRANSFEROWN	-	-
WAGESTD	Calculated using equation (4.5)	-0.0007
WAGESTD*RBBT	Calculated using equation (4.5)	0.0013
WAGESTD*BOTH	Calculated using equation (4.5)	0.0015
FL	Calculated using equation (4.6)	-0.2072
GA	Calculated using equation (4.6)	0.1854

Note: Marginal effects calculated at the sample average of covariates

The marginal effects of years of experience (*YEARS*) reveal each yearly increase in experience increases the probability of MHT adoption by 0.004 until the inflection point at 19 years. Increasing years of experience captures management efficiency and learning, and is generally hypothesized to increase the probability of technology adoption (Fernandez-Cornejo, Beach and Huang, 1994). The production variable captures the effect of farm size and yield. Marginal effects show that for Rabbiteye production every 1,000 pound increase in production increases the probability of MHT adoption by 0.0010.

For farmers who diversify to both cultivars, the marginal effects indicate that every 1,000 pound increase in production increases the probability of MHT adoption by 0.0015. The marginal effect for Southern Highbush production is nearly insignificant at 0.0001 for every 1,000 pound increase. The mean production for the observed Rabbiteye only producers was 74,137 lbs. per orchard while the mean production for the observed both cultivar producers was 699,246 lbs. per orchard.

The larger increase in the probability of MHT adoption for increases Rabbiteye and both cultivar production than the probability of MHT adoption for increases in Southern Highbush production is most likely due to berry characteristics and mechanical harvester innovations. As noted in the introduction, the Rabbiteye cultivar has firmer flesh and fruit, thus less likely to be damaged during mechanical harvesting. It also ripens later in the season and can encounter competition from other blueberry producing regions that will lower farm-gate fresh market prices, inducing Southeastern producers to shift away from hand harvesting as a cost saving measure. Experimentation and field trials with mechanical harvesters on Southern blueberry cultivars has existed since the mid 1990's, but were only effective[6] on Rabbiteye varieties at that time. Effective mechanical harvesting of Southern Highbush varieties based on experiments and field trials was acknowledged a decade later in the mid 2000's as innovations in variety characteristics and harvester mechanics improved (Takeda, et al., 2008; Safley, Cline and Mainland, 2006).

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[6] Effective is defined as not damaging the bush to the point of reducing yields the following year, or excessively bruising and popping the fruit.

Number of crop insurance purchases in the last ten years explicitly measures risk preference where a risk loving farmer would be hypothesized to not purchase crop insurance, a slightly to moderately risk averse farmer would be hypothesized to purchase crop insurance a few times in a ten year period, and a very risk averse farmer would be hypothesized to purchase crop insurance as often as possible. Because the variables for crop insurance purchases are dummies, (*CROPINS2*) and (*CROPINS4*), the marginal effects change likelihood of MHT adoption from the position of no crop insurance purchased. Thus, one to six crop insurance purchases increases the likelihood of MHT adoption by 0.0677 and seven to ten crop insurance purchases increase the likelihood of MHT adoption by 0.3183. The marginal effect for seven to ten crop insurance purchases is the largest effect among the dummy variables in the model. This explicit risk preference variable suggests risk-averse blueberry farmers are more likely to adopt MHT technology than risk neutral or risk loving farmers. This implication however is not confirmed by the signs or magnitudes of the marginal effects of the implicit risk preference variables: (*WTARISK2*), (*WTARISK3*), and (*WTARISK4*).

The marginal effect for standard deviation of wages for Southern Highbush only growers (*WAGESTD*) reveals an increase in wage variation decreases the probabilities of MHT adoption. This marginal effect for Rabbiteye only growers (*WAGESTD*RBBT*) is 0.0013, thus a one hundred dollar increase in the standard deviation of wages for Rabbiteye only growers increases the likelihood of MHT adoption by 0.13. The marginal effect for growers of both cultivars (*WAGESTD*BOTH*) is 0.0015. A one hundred dollar increase in the standard deviation of wages increases the likelihood of MHT adoption for growers of both cultivars by 0.15.

Table 5.3 shows results of what is referred to as the ex-ante consideration model. This is a binomial logit regression with the dependent variable *Y*=1 if non-MHT adopters would consider using MHT in the next five years and 0 otherwise. The regression was estimated using the same independent variables[7] as the MHT adoption model. Measures of goodness of fit indicate a good fit for a small sample size with Cox and Snell R^2 values of 0.333 for less than a [0,1] interval and rescaled to a [0,1] interval of 0.445. Values of Akaike's Information Criterion (AIC), Schwartz Criterion (SC), and -2Log L value of 80.035 establish a better model fit for the covariates than alternative model formulations.

[7] Willingness to accept risk discrete variable (*WTARISK3*) was combined with (*WTARISK2*) due to low number of observations

Table 5.3 Binomial Logit Model of MHT Consideration in Next Five Years among Non-Adopters

Variable	Description	Coefficient	Std. Error
INTERCEPT	-	9.862	10.380
YEARS	Years of experience	0.088	0.199
YEARSQ	-	-0.007	0.008
AGE	Age of the farmer	-0.420	0.391
AGESQ	-	0.004	0.004
PROD	Southern Highbush production only (by default)	0.008***	0.004
PROD*RBBT	Rabbiteye production only	0.007	0.020
PROD*BOTH	Both cultivar production	-0.012	0.046
CROPINS2	1-6 purchases in last 10 years	-1.048	0.917
CROPINS4	7-10 purchases in last 10 years	1.363	1.668
WTARISK2	Low and Med WTA risk compared to peers	1.153	0.919
WTARISK4	High WTA risk compared to peers	0.955	1.041
TRANSFEROWN	Plan to transfer ownership to associate	0.473	0.379
WAGESTD	Southern Highbush St. Dev. of wage (by default)	-0.009	0.012
WAGESTD*RBBT	Rabbiteye farms St. Dev. of wage	0.015	0.015
WAGESTD*BOTH	Farms with both cultivars St. Dev. of wage	-0.008	0.019
FL		-1.760***	1.068
GA		0.878	1.146
Number of Observations	82		
Percent Concordant	82.36		

Note: *, **, *** denotes statistical significance at the 20%, 15% and 10% levels, respectively for the Consideration model. Standard errors are conventionally calculated using a Taylor series approximation

Figure 5.4 shows the ROC Curve for the ex-post consideration model which displays the goodness of fit using concordant pairs of predicted pairs versus actual pairs. The curve shows that 82.36 percent of the actual pairs were accurately predicted.

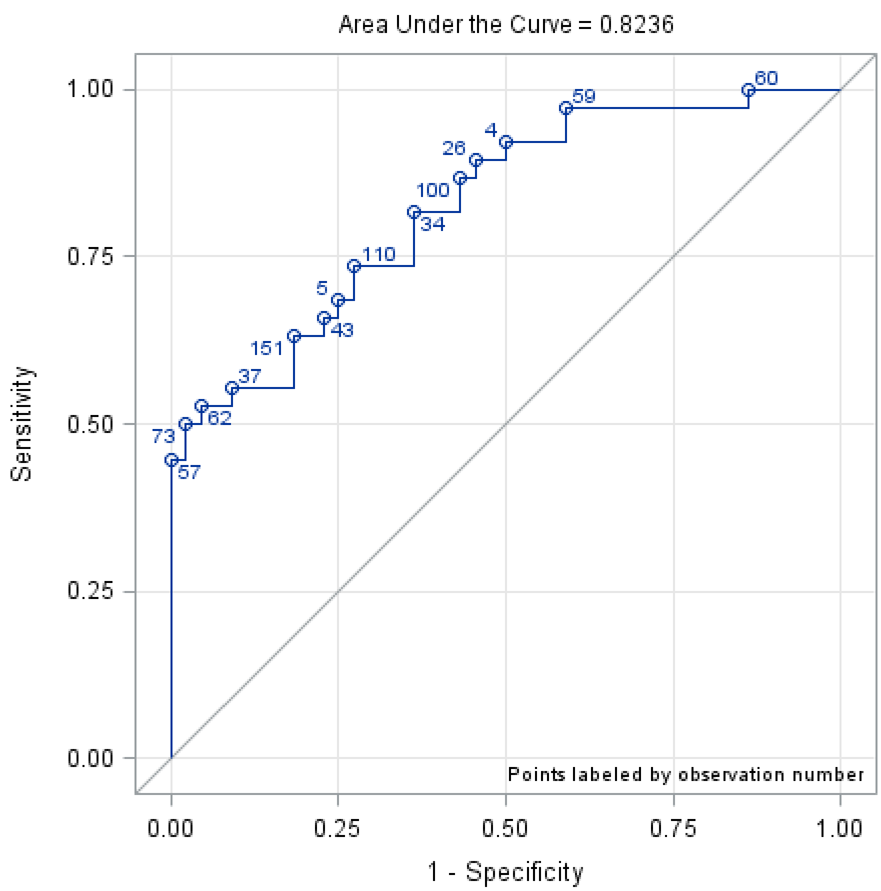

Figure 5.4 ROC Curve for ex-post consideration model

Statistical significance is reduced for the ex-ante consideration model as the sample size is much smaller compared to the sample for the adoption model. Although noise exists within the ex-ante consideration model, the ROC curve provides evidence that the model is not a completely ill-defined measure of future adoption behavior.

Among non-MHT adopters, only production of Southern Highbush and farming in Florida were significant. Increases in Southern Highbush production among current non-adopters increase the likelihood of considering MHT adoption within five years. Among current non-adopting farmers, Florida farming decreases the likelihood of considering MHT adoption. These findings support the indication that blueberry farmers are aware that MHT innovations, with regards to the more sensitive Southern Highbush berries, will become efficient within five years of the survey. However, non-adopting Florida farmers, many whom grow early season Southern Highbush or diversified orchards, seem unwilling to take into account MHT innovation efficiencies.

The coefficients of the ex-ante consideration model from Table 5.3 and the coefficients of the ex-post adoption model presented on Table 5.1 are presented on Table 5.4. The signs of the coefficients of the continuous variables and the direction of the coefficients of the dummy variables are compared in order to determine if the variables present robustness among ex-ante and ex-post observations.

Table 5.4 Coefficient Comparison for the Consideration Model and the Adoption Model

Variable	**Description**	**Ex-Post Adoption Model**	**Ex-Ante Consideration Model**
INTERCEPT	-	-38.318***	9.862
YEARS	Years of experience	0.176***	0.088
YEARSQ	-	-0.005***	-0.007
AGE	Age of farmer	1.157**	-0.420
AGESQ	-	-0.010**	0.004
PROD	Southern Highbush production only	0.001	0.008***
PROD*RBBT	Rabbiteye production only	0.017**	0.007
PROD*BOTH	Both cultivar production	0.031***	-0.012
CROPINS2	1-6 purchases in last 10 years	1.128*	-1.048
CROPINS4	7-10 purchases in last 10 years	6.297***	1.363
WTARISK2	Low and Med WTA risk compared to peers	0.916	1.153
WTARISK3 (Adoption Model)	Med WTA risk compared to peers	0.398	-
WTARISK4	High WTA risk compared to peers	1.471	0.955
TRANSFEROWN	Plans to transfer ownership to associate	-0.214	0.473
WAGESTD	Southern Highbush St. Dev. of wage only	0.022	-0.009
WAGESTD*RBBT	Rabbiteye farms St. Dev. of wage	-0.009*	0.015
WAGESTD*BOTH	Farms with both cultivars S.D. of wage	0.026**	-0.008
FL	Florida farms only	-5.135**	-1.760***
GA	Georgia farms only	3.112***	0.878
Number of Observations		202	82
Percent Concordant		97.56	82.36

Note: *, **, *** denotes statistical significance at the 20%, 15% and 10% levels, respectively for the Consideration model. *, **, *** denotes statistical significance at the 15%, 10% and 5% levels, respectively for the Adoption model

The direction of the relationship between adoption and years of experience is the same in both models. The direction of the relationships between adoption and production of Southern Highbush only and Rabbiteye only farms are the same in both models. Similarly, the relationship between adoption and crop insurance purchases, the observed measure of risk preference, display the same general direction. Fewer purchases have a lower likelihood of MHT adoption than many purchases, which have a higher likelihood of MHT adoption for both ex-ante and ex-post models. Willingness to accept risk as compared to peers, the stated measure of risk preference, did not display significance nor directional consistency between the two models. This lack of significance could be related to noise in self reporting risk preferences, as well as a non-descript peer group.

The signs of the standard deviation of wage estimates changed for all three coefficients between both models. However, the signs for the coefficients for Florida and Georgia remained the same for the ex-ante and ex-post models. This result could signal that wage variation is significant in determining MHT adoption ex-post, but for non-adopters wage variation has little effect on adoption probabilities ex-ante. However, region has better predicting power ex-ante and ex-post than wage variation.

The results of the adoption model demonstrate the strong predictive power for the variables used in estimating the probability of adoption ex-post. However, when those variables are used ex-ante, their predictive power decreases. This should be expected as noise is inherent in logit regressions of small sample sizes, and that the ex-ante consideration model is attempting to predict a reaction to a future behavior. Regardless, estimating probabilities of adoption using both an ex-post and ex-ante model improves the temporal component of adoption modeling using a cross-sectional survey when a time-series survey is not available.

CHAPTER VI

CONCLUSIONS

The results of this study provide insight into motivations that influence the adoption of MHT among Southeastern blueberry growers. Furthermore, this study attempts to find if the factors that influence MHT adoption in the present are the same motivations for future MHT adoption among growers that currently do not use mechanical harvesting. The analysis indicates that variables such as experience, age, and farm size behave similarly as in previous studies in the technology adoption literature. However, technology adoption literature assumes that risk aversion leads to a decreased likelihood of technology adoption. Our analysis indicates that the opposite is true; Southeastern blueberry growers who display higher risk aversion preferences have increased likelihood of adopting mechanical harvesting technologies. One hypothesis 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 seasonal manual labor, which due to the current state of patchwork immigration policy and enforcement, availability is becoming more volatile. Conversely, currently adopting new mechanical harvester technology is still unproven economically for many of the premium price Southeastern blueberry cultivars. Our analysis reveals that risk-averse Southeastern blueberry producers are more willing to accept the risks inherent in the new technology than accept the risks currently associated with the status quo.

Our analysis finds that wage instability, measured by county-level standard deviation of weekly wages for farm workers, does not have the same effect in terms of magnitude in the likelihood of MHT adoption as risk preference and geographic variables. However, standard deviation of wage variables are significant for Rabbiteye growers and diversified growers in the ex-post model. These growers are more likely to use MHT as their wage volatility increases on crops that have a longer history and more available data of MHT usage. For these growers who may not receive high early season farm-gate prices, MHT provides cost reliability compared with hand harvesting, even if the grower may expect lower revenues than hand harvesting. This cost reliability is increasingly important to growers as the margin between operating costs and revenues narrows as each season progresses.

The likelihood of MHT usage and consideration decreases among Florida growers. This negative effect could be due to the premium price that Florida growers receive in the earliest part of the season, combined with uncertainty about the quality and quantity of yields that common machine harvesters produce on fresh market product. The Florida agricultural market also has longer seasonal need for farm laborers due its late winter citrus harvest, unique within the Southeastern region. High early season farm gate prices and higher labor availability compared with other Southeastern states explain Florida blueberry farmer's decreased likelihood of harvester adoption.

Conversely, the likelihood of MHT adoption and consideration increases among Georgia growers. This increase in the likelihood of harvester usage is due to MHT providing more certainty in terms of availability than seasonal farm laborers in the state. Georgia has enacted state and local legislation that has directly caused labor shortages and increased wage variability for specialty crop growers within the state. Under these circumstances labor availability decreases, wage volatility increases, and increase Georgia farmers' likelihood of adopting MHT.

This seasonal labor availability may have an even larger impact on harvesting technology decisions for blueberry farmers, as farmers forecast their future revenue streams. Non-adopting Florida farmers have a decreased likelihood of intending to use MHT adoption within five years of the survey compared with growers in Georgia, Mississippi and North Carolina. Although strict immigration legislation is currently pending in their state, they seem to have faith that the profitability they uniquely enjoy using seasonal laborers outweighs the risks of potential labor unavailability. For current non-adopting Georgia growers, being a Georgia grower increases the likelihood of considering adopting MHT within five years compared with other Southeastern blueberry states. One reason for this may be that Georgia growers appear to acknowledge documented labor unavailability and increased enforcement, and are increasingly unwilling to accept the risk associated with highly profitable hand-picked blueberries in lieu of the less profitable, but more reliable, machine harvesting technologies.

The removal of uncertainty related to labor markets would allow blueberry growers to choose between hand harvesting at a stable wage rate or adopting machine harvesting technology primarily based benefit cost analysis. Until this uncertainty is removed, blueberry growers are going to face uncertain labor markets and incorporate wage volatility and labor availability in their harvesting technology decisions.

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APPENDIX A

2011 BLUEBERRY INDUSTRY SURVEY

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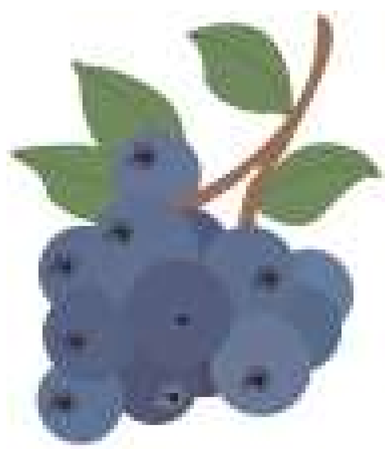

Q1. In what County are the majority of your blueberry acres located?

_____________ COUNTY

Q2. How many years have you been growing blueberries?

_________ NUMBER OF YEARS GROWING BLUEBERRIES

Q3. How many acres of blueberry land did you own in 2010?

_________ NUMBER OF BLUEBERRY ACRES OWNED IN 2010

Q4. How many acres of blueberry land did you lease in 2010?

_________ NUMBER OF BLUEBERRY ACRES LEASED IN 2010

Q5. Since 2005, have you acquired new land to grow blueberries?

☐ NO, I HAVE NOT ACQUIRED NEW LAND TO GROW BLUEBERRIES SINCE 2005

☐ YES, I ACQUIRED NEW LAND TO GROW BLUEBERRIES IN ________ (YEAR)

Q6. Have you ever used any of the information sources listed below? Please circle all sources that you have used. If you use an information source that is not listed, please add it to the OTHER category and specify the information source.

A. OTHER BLUEBERRY GROWERS

B. UNIVERSITY PERSONNEL

C. INTERNET WEBSITE (SPECIFY ____________________________________)

D. BROKER/COOPERATIVE

E. NORTH AMERICAN BLUEBERRY COUNCIL

F. STATE GROWER ASSOCIATION

G. OTHER (SPECIFY ____)

Q7. Of the possible information sources listed in Q6, which do you feel are the most important? *(Please write the LETTER from Q6 in the appropriate box)*

☐ MOST IMPORTANT ☐ 2ND MOST IMPORTANT ☐ 3RD MOST IMPORTANT

Q8. For 2011, please indicate your expected LOW, AVERAGE and HIGH yields and prices for fresh and processed blueberries:

2011 BLUEBERRY PRICE AND YIELD EXPECTATIONS

	LOW	AVERAGE	HIGH
EXPECTED YIELD	________LBS./ACRE	________LBS./ACRE	________LBS./ACRE
EXPECTED FRESH PRICE	$ ________ PER LB	$ ________ PER LB	$________ PER LB
EXPECTED PROCESSED PRICE	$ ________ PER LB	$ ________ PER LB	________ PER LB

Q9. Relative to other blueberry growers, how would you describe your willingness to accept RISK in your blueberry farm business? *Circle the number that best represents your answer.*

0--------------------1--------------------2--------------------3--------------------4

[MUCH LESS WILLING ------------------------------------ MUCH MORE WILLING]

Q10. Relative to other blueberry growers, how concerned are you about AVERAGE blueberry prices during 2011 season? *Circle the number that best represents your answer.*

0--------------------1--------------------2--------------------3--------------------4

[MUCH LESS CONCERNED -------------------------- MUCH MORE CONCERNED]

Q11. Relative to other blueberry growers, how concerned are you about the stability/variation of blueberry prices during 2011 season? *Circle the number that best represents your answer.*

0--------------------1--------------------2--------------------3--------------------4

[MUCH LESS CONCERNED ------------------------ MUCH MORE CONCERNED]

	2010 conventional rabbiteye	2010 organic rabbiteye
total acres	______________acres	______________acres
average yield	___________ lbs./acre	___________ lbs./acre
sold fresh	___________percent	___________ percent
fresh price received	$ ___________ per lb	$_____________ per lb
process price received	$ ___________ per lb	$ ____ ________ per lb

Q12. For your 2010 RABBITEYE production, complete the table for CONVENTIONAL and ORGANIC production *(If you did not produce rabbiteyes, SKIP TO Q13)*:

Q13. For your 2010 HIGHBUSH production, complete the table for CONVENTIONAL and ORGANIC production:

	2010 CONVENTIONAL HIGHBUSH	**2010 ORGANIC HIGHBUSH**
TOTAL ACRES	___________________ACRES	_____________ACRES
AVERAGE YIELD	________________ LBS./ACRE	__________ LBS./ACRE
SOLD FRESH	________________ PERCENT	__________ PERCENT
FRESH PRICE RECEIVED	$ _______________ PER LB	$ __________________ PER LB
PROCESS PRICE RECEIVED	$ _______________ PER LB	$ __________________ PER LB

Q14. In 2010, did you hand-pick any of your blueberry plants?

☐ NO -- HOW LIKELY ARE YOU TO CONSIDER HAND PICKING YOUR BLUEBERRIES IN THE NEXT FIVE YEARS? *PLEASE CIRCLE THE NUMBER INDICATING YOUR LIKELIHOOD*:

0----------------1----------------2---------------3----------------4

[VERY UNLIKELY -- VERY LIKELY]

☐ YES -- PLEASE INDICATE THE FOLLOWING CONCERNING YOUR HAND-PICKED BLUEBERRIES:

HAND-PICK RABBITEYES? ________________ NUMBER OF ACRES

HAND-PICK HIGHBUSH? __________________ NUMBER OF ACRES

Q15. In 2010, did you machine harvest any of your blueberry plants?

☐ NO -- HOW LIKELY ARE YOU TO CONSIDER MACHINE HARVEST OF YOUR BLUEBERRIES IN THE NEXT FIVE YEARS? *PLEASE CIRCLE THE NUMBER INDICATING YOUR LIKELIHOOD*:

0----------------1----------------2---------------3----------------4

[VERY UNLIKELY -- VERY LIKELY]

☐ YES -- PLEASE INDICATE THE FOLLOWING CONCERNING YOUR MACHINE-HARVESTED BLUEBERRIES:

MACHINE HARVESTED RABBITEYES? ________________NUMBER OF ACRES

MACHINE HARVESTED HIGHBUSH? __________________ NUMBER OF ACRES

MACHINE HARVESTERS YOU OWN: __________ NUMBER OF MACHINES OWNED

MACHINE HARVESTERS YOU LEASE: __________ NUMBER OF MACHINES LEASED

Q16.In 2010, did you plant or produce organic blueberries? *Check all that apply:*

- ☐ NO -- how likely are you to CONSIDER planting organic blueberries in the NEXT FIVE years? *Please circle the number indicating your likelihood*:

  0-----------------1-----------------2---------------3----------------4
  [Very Unlikely -- Very Likely]
- ☐ YES, planted organic blueberries in 2010______________ number of acres
- ☐ YES, produced organic blueberries in 2010____________ number of acres

Q17.For 2010, please indicate the percentage of your blueberry production you sold through each of the marketing channels. *Check that your responses total 100% of your total 2010 blueberry sales.*

2010 BLUEBERRY SALES	PERCENT OF TOTAL 2010 SALES
2010 SALES TO COOPERATIVE..............................	____________________ PERCENT
2010 SALES TO WHOLESALER (BROKER)..................	____________________ PERCENT
2010 SALES DIRECT TO FINAL CUSTOMER................	____________________ PERCENT

Q18.Thinking about each of these same marketing channels, how satisfied or dissatisfied were you with each channel that you used in 2010? *Circle your*

2010 MARKETING CHANNEL	HOW SATISFIED? (PLEASE CIRCLE)		
WHOLESALER (BROKER)	NOT	SOMEWHAT	VERY
DIRECT TO FINAL CONSUMER	NOT	SOMEWHAT	VERY

level of satisfaction with each marketing channel that you used in 2010.

Q19. In 2010, did you use any of these technologies? *Check all that apply:*

- ☐ Drip-tape irrigation
- ☐ Overhead irrigation
- ☐ Soil analysis
- ☐ Plant leaf analysis
- ☐ Wind machines
- ☐ High tunnels

Q20. Thinking about each of these same technologies, do you plan to implement any of these in the next five years? *Circle YES or NO as it applies for each technology.*

TECHNOLOGY	PLAN TO IMPLEMENT IN NEXT FIVE YEARS? (PLEASE CIRCLE)		
DRIP TAPE IRRIGATION	YES	NO	DON'T KNOW
OVERHEAD IRRIGATION	YES	NO	DON'T KNOW
SOIL ANALYSIS	YES	NO	DON'T KNOW
PLANT LEAF ANALYSIS	YES	NO	DON'T KNOW
WIND MACHINE	YES	NO	DON'T KNOW
HIGH TUNNELS	YES	NO	DON'T KNOW

Q21. Do you have onsite cold storage facilities?

- ☐ NO, I DO NOT HAVE ONSITE COLD STORAGE
- ☐ YES, I HAVE ONSITE COLD STORAGE, APPROX. _________ SQ FT.

Q22. How often have you purchased blueberry crop insurance in the last ten years?

- ☐ NO, I HAVE NEVER PURCHASED BLUEBERRY CROP INSURANCE SINCE 2000
- ☐ YES - 1 TO 3 TIMES SINCE 2000

- ☐ YES - 4 TO 6 TIMES SINCE 2000
- ☐ YES - 7 TO 9 TIMES SINCE 2000
- ☐ YES - 10 TIMES SINCE 2000

Q23. In 2010, what percent of your blueberry land and establishment costs were financed?

_______________ PERCENT BLUEBERRY LAND/ESTABLISHMENT COSTS FINANCED IN 2010

Q24. Upon your retirement, do you plan to transfer ownership of your blueberry operation to family or non-family member? *Please check all that apply:*

- ☐ NO, I DO NOT PLAN TO TRANSFER OWNERSHIP TO ANYONE
- ☐ YES, I DO PLAN TO TRANSFER OWNERSHIP TO FAMILY MEMBER
- ☐ YES, I DO PLAN TO TRANSFER OWNERSHIP TO NON-FAMILY MEMBER

Q25. For 2010, please complete the table indicating the number of family and non-family members employed in each stage of your blueberry operation. *(If someone works in more than one category, please indicate the category where that person dedicates the majority of their time):*

	FAMILY		NON-FAMILY	
	(# FULL-TIME)	(# PART-TIME)	(# FULL-TIME)	(# PART-TIME)
PRE-HARVEST – FIELD				
HARVEST - PICKERS				
HARVEST - PACKING				
MANAGEMENT				
OTHER__________				

Q26. Indicate the percentage of your 2010 family income that was generated from each of the following employment opportunities:

2010 FAMILY INCOME	PERCENT OF 2010 FAMILY INCOME
2010 GENERATED FROM BLUEBERRY PRODUCTION	______________ PERCENT
2010 GENERATED FROM OTHER FARM PRODUCTION	______________ PERCENT
2010 GENERATED FROM OFF-FARM EMPLOYMENT	______________ PERCENT

Q27. What is the highest level of education that you have completed?

- ☐ Some high school
- ☐ completed high school
- ☐ Some college
- ☐ completed college
- ☐ some graduate school
- ☐ completed graduate degree

Q28. Are you:

- ☐ MALE
- ☐ FEMALE

Q29. Please indicate your age range?

- ☐ 18-24 years
- ☐ 25-34 years
- ☐ 35-44 years
- ☐ 45-54 years
- ☐ 55-64 years
- ☐ 65 years and up
- ☐

Q30. Please select your race:

- ☐ Black/African-American
- ☐ White
- ☐ Asian
- ☐ American Indian/Aleut
- ☐ Other ________________(please specify)

Q31. Would you say you are of Hispanic ancestry?

- ☐ YES
- ☐ NO

Q32. Just for statistical purposes, please indicate your 2010 blueberry operation gross sales (before taxes).

- ☐ UNDER $10,000
- ☐ $10,000 TO $24,999
- ☐ $25,000 TO $49,999
- ☐ $50,000 TO $99,999
- ☐ $100,000 TO $199,999
- ☐ $200,000 TO $499,999
- ☐ $500,000 TO $999,999
- ☐ $1 MILLION OR MORE

Q33. Listed below are some ideas suggested as possible goals for future research priorities. Please indicate whether you feel that each goal should NOT be a priority, should be given a LOW priority, MEDIUM priority, or HIGH priority:

GOAL NUMBER	POSSIBLE RESEARCH	HOW MUCH PRIORITY, IF ANY, SHOULD EACH GOAL HAVE? (PLEASE CIRCLE YOUR ANSWERS)			
1	WEED CONTROL	NOT	LOW	MEDIUM	HIGH
2	INSECT CONTROL	NOT	LOW	MEDIUM	HIGH
3	LABOR REGULATIONS	NOT	LOW	MEDIUM	HIGH
4	CONSUMER DEMAND	NOT	LOW	MEDIUM	HIGH
5	FOOD SAFETY REGULATIONS	NOT	LOW	MEDIUM	HIGH
6	INCREASE CONSUMER DEMAND	NOT	LOW	MEDIUM	HIGH
7	GOVERNMENT REGULATIONS	NOT	LOW	MEDIUM	HIGH
	ARE THERE ANY OTHERS? (PLEASE LIST BELOW):				
8	______________________	NOT	LOW	MEDIUM	HIGH
9	______________________	NOT	LOW	MEDIUM	HIGH

THANKS SO VERY MUCH FOR TAKING THE TIME TO COMPLETE THIS SURVEY. YOUR RESPONSES WILL SERVE TO FOCUS RESEARCH EFFORTS TOWARDS PROFITABLE ALTERNATIVE SUGGESTIONS FOR MEMBERS OF THE BLUEBERRY INDUSTY IN SOUTHEASTERN U.S.