Cultivating compensation: How technology skills and job attributes affect salary in agricultural jobs

by

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Abstract

Technological advancements are transforming the agricultural industry, creating new workforce demands and altering the skills required for employment. This study examines the relationship between technology, skill requirements, education, and salary outcomes in the U.S. agricultural labor market. Job posting data were collected through automated web scraping from online employment platforms and analyzed using text analysis techniques to construct measures of technology intensity, manual skills, and soft skills. Occupations were classified according to their technological content and linked with salary and job characteristic information.

Three econometric approaches were employed to evaluate salary determinants: ordinary least squares (OLS), ordered logit, and Heckman selection models. The OLS models estimated the effects of technology, skills, education, occupation, geography, and posting characteristics on salary levels. Ordered logit models examined the factors influencing movement across salary categories, while Heckman selection models corrected for potential bias resulting from the selective disclosure of salary information in job postings.

The results indicate that education and skill composition are stronger predictors of salary outcomes than technology alone. Across most specifications, manual and soft skills were positively associated with salary, while higher levels of educational attainment consistently generated substantial wage premiums. Technology variables produced mixed results in the OLS and ordered logit models, suggesting that technological intensity alone does not explain salary variation across agricultural occupations. However, after accounting for salary disclosure bias through the Heckman selection framework, advanced technology positions were associated with

higher compensation, indicating that technology-related wage premiums may be partially obscured by selection effects.

Overall, the findings suggest that modernization within agriculture is increasing demand for workers who possess a combination of technical, manual, and soft skills, supported by higher levels of education. These results provide valuable insights for students, job seekers, employers, and educational institutions seeking to understand workforce needs in an increasingly technology-driven agricultural sector. The study contributes to the growing literature on agricultural labor markets by highlighting the continuing importance of human capital alongside technological advancements.

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Dedication

This thesis is dedicated to my mother, whose love and strength shaped who I am and continues to guide me through every challenge. Even though you cannot be here to witness this accomplishment, I hope I have made you proud.

Chapter 1 - Introduction

According to the U.S. Bureau of Labor, there are over 160 million people in the workforce in America (Statistics, 2025). Of course, the workforce is made up of many different types of jobs and sectors, and technology has impacted many of those and in different ways. Agriculture is one sector that is especially impactful on the United States economy, farms produce about 0.8% or $222.3 billion of the US gross domestic product (GDP). Many other industries like food and beverage, clothing, leather products, forestry and fishing rely on the agriculture industry as well. Together, these account for about 5.5% of the US GDP or $1.537 trillion, showing that increasing technologies and efficiency in the agriculture sector in the United States could be very impactful (Zahniser, 2024). Data USA shows over 562,000 workers in the agricultural sector in 2022, a 2% increase from the year prior. There were 50,000 agricultural degrees earned by students in 2022 just from public 4-year institutions in the U.S., which is encouraging because the average age of the agricultural workforce is 44 years old, so it will be important that this younger group stays within the agriculture industry (Data USA, 2022). However, if we know how technology skills can be implemented into agriculture so that it is used most effectively, we could increase the productivity and efficiency of the industry even with a decreasing number of workers wanting to enter. We can also better prepare the future workforce with the skills and knowledge needed and prepare the industry to become and stay successful.

Another reason why knowing the impact of technology on the labor force is important is because the labor force is changing. For instance, consider the impact of immigrant labor in agriculture. 68% of the United States agriculture workforce is made up of immigrant farm workers (Castellanos-Canales, 2022). Many migrant laborers are used for seasonal work and high labor jobs that are paid low wages, which if labor continues to be available at those low wages, there is little incentive for producers to implement technology (Charlton & Kostandini, 2021; Charlton, 2025). If policies prevent or discourage immigrants from coming into the United States, this will greatly affect wage rates and labor availability in the sector. There is already a decreasing number of United States citizens that want to work in agriculture let alone in those laborious positions (Charlton, 2025). If we are able to implement more technology to do some of those jobs, this will help those agricultural employers that now are not able to hire migrant workers and cannot find replacement labor within US citizens.

There have been many different types of technology implemented foe various purposes in agriculture. Examples include robots that can pick strawberries (Charlton, 2025) and other delicate produce, drones used to spray fertilizers, herbicides, insecticides, fungicides and more over crops and land, soil sensors that can read the soils PH, moisture and fertility levels and Global Positioning Systems (GPS) that can guide farm machinery and yield map fields (Ovie, 2025). This technology can help the owners of agriculture businesses to be more efficient and produce less waste. As the number of people in the world increases, this means that agriculture must continue to become more efficient to produce more food for the population using the same or less land and other inputs. Technology helps us to be more efficient in the production of food. It also can create more higher skilled, less labor intensive jobs that more U.S. workers may be interested in. However, this technology can be expensive, and some do not have the funds to implement this technology, causing them to fall farther behind their counterparts. There are some programs in place like the PRECISE, LAST ACRE, and PAL acts that are helping to make some of this technology more affordable and available for a larger number of agricultural workers and update the infrastructure needed (Fischer, 2025).

Another reason implementing technology into the agriculture sector is important is because of inflation. The inputs that farmers need to produce food have increased, thus the price of food has also increased. In the U.S. there has been about an 11% increase in the price of food from 2021 to 2022 (Castellanos-Canales, 2022). This is greatly affecting the American people and what they are able to purchase. This is in part due to labor shortages that cause a decrease in the output the agriculture sector is able to produce. With the implementation of technology, agriculture production owners would be able to fill the void of the decreased number of workers and help make them more efficient and productive. Thus, they should be able to produce more, and this will help to decrease the price consumers will pay eventually.

In this research, we will answer the question: How do different job attributes and technology affect salaries within the agricultural job market?

Chapter 2 - Literature Review

The research on the agricultural labor market has been limited to this point. This section describes the literature on the mobility of agricultural workers, immigrant labor, technological advancements, and the skills needed.

Agricultural Labor

Barkley (1991) explained that types of training, gender, and rural and urban lifestyles affect the mobility of an employee. If an employee only has general training, they have increased mobility because their skills can transfer to other jobs, whereas if they have specific training, they are less likely to leave the job and are a higher investment for the company. He also found that women are less mobile than men because they are expected to work for a shorter total amount of time throughout their careers before starting a family and potentially staying home with the children. Rural workers are also less mobile than urban workers because they are believed to be less likely to give up the rural lifestyle compared to urban workers, who also have many options constantly becoming available because of their location and their qualifications.

Preston et al. (1990) examined the relationship between the education that agricultural students received and the income they received. This paper found that things like performance in college and personal background were used to measure a potential employee's potential success on the job when hired right out of college, but these things seemed to become less important as the employee’s career progresses. Also, as expected, students who completed graduate education programs made more than those who had bachelor's degrees or less, and when looking at salaries geographically, they were higher outside of the Southern region of the United States.

Immigrant Labor

While the agricultural industry is very diverse, there are some sectors that are very labor-intensive and over the years, the supply of workers has declined. While some workers migrate to other lower labor jobs, some leave the industry all together. One way the agriculture industry has dealt with this decrease in laborers is by using immigrant labor. Charlton and Kostandini (2021) mention the use of migrant workers in the dairy industry. Due to increased immigration regulations, like the 287 (g) policies, there are fewer immigrants from Mexico coming to work in agriculture at a decreasing rate of about 1% every year, thus, the adoption of new technologies will be imperative for farms to stay competitive. They found that there was a 17-31% increase in labor productivity after the 287 (g) policies were put into place; they suggest this is partially due to increased technology advancements within the dairy industry.

Ifft and Jodlowski (2022) also examine the impacts of the 287 (g) policies on the local agriculture industry. Their results indicate that the 287 (g) policies do negatively affect the labor supply, farms are forced to become more machine intensive and there is a limited substitutability for immigrant farm workers. As expected, larger farms are able to adjust to the labor supply shock better and as a result small farms decrease. While some technology implementation can help mitigate the impact of the supply decrease, they found that technology and domestic workers cannot completely compensate from immigrant workers. However, these challenges could be the reason there are more investments into technology and robotics in the agricultural sector specifically (Ifft & Jodlowski, 2022).

Charlton (2025) talks about the use of unauthorized immigrants in the more intensive crop production sector for products like fruits, vegetables and horticultural products because they are willing to do seasonal and routine tasks that many U.S. citizens would not. The crop workers in the United States are over a third made up of unauthorized immigrants in 2022 because more U.S. workers are moving to jobs off the farm and immigrants are moving in and filling the gap starting in the 20th century. However, recently there has been talk of implementing strict immigration policies on the federal level and until now, policies like these have only been implemented at the state level. With this causing a potential major decrease in the unauthorized immigrant labor supply, this will cause those labor-intensive farms to invest in technology, but this is not a perfect substitute for labor in the short run because of the limitations that face technology as compared to humans doing the same job. This has also caused Congress to examine expanding the H-2A guest agricultural worker program from including only seasonal work, however being proposed multiple times since 2019 has never been approved. In 2012, there were 85,000 H-2A workers and this number grew to 378,000 in 2023 with a continued increase expected for 2025.

Technology

Another way the agriculture industry deals with the decreased number of farm workers is by adopting innovations and mechanisms in their production. Huffman (2005) talks about the increased use of technology in the agriculture industry, which in turn, allows for fewer workers needed. For instance, new technologies implemented since the 1950s have decreased the farm labor needed, decreasing from 10 million workers in 1950 to 3 million in 2000. Christiaensen et al. (2020) said that this increase in technology is going to reduce the need for manual labor, but it will also create new jobs within the technology industry. The United States needs to create policies to help smooth the transition and help with the labor displacement and skill gaps of workers. The future workers will also need to be technology savvy to effectively adopt and use the technology. Christiaensen et al. (2020) argue that agriculture tasks are more able to be automated because of their routine and require fewer cognitive skills, and because of this, the agriculture industry could be transformed. These changes of technology adoption could decrease input costs, change economies of scale, and change the most efficient capital/labor ratio in production, processing, and marketing. Productivity will continue to increase, and we will be able to produce more food with fewer agricultural workers. However, with these changes, the workforce will need to be "tekked up" to run an efficient "tekked up" industry, and this will require some skill-building and extension programs to help create "tekked up" workers (Christiaensen et al., 2020). Rotz et al. (2019) bring up a few concerns with the innovations of technology being adopted into agriculture. Could this technology create more problems for the agriculture industry? It could increase land degradation, capital accumulation, and the exploitation of laborers by large-scale adopters. It could create a larger gap in access to technology and information, which could create uneven development across the industry.

Wang et al. (2021) brings up the possibility that farms could be unmanned over the next 50 years, with improvements on sensor reliability, robot efficiencies, and AI complex settings and policy support, subsidies and investments into research and development. Along the same lines, McFadden et al. (2023) like the innovations available to agriculture to improve basic farming practices like planting, fertilizing, and monitoring. But they do warn that there are barriers to implementing these types of technology that may put it out of reach for some farmers. Things like high costs, data overload, and rural broadband access are major problems. Bessen (2015) explains that within the automation process that agriculture is likely to adopt, there are two types: partial and complete automation. He argues that total automation creates a loss of jobs within the industry, but partial automation increases or shifts jobs to other industries because the demand for jobs is inelastic, or automation can be a substitute for jobs.

There have been some technology advancements to create robots that can pick strawberries and apples, but these robots are still less efficient than the human workers and more expensive that the wages that unauthorized immigrants and other seasonal workers will accept. However, there may be increased incentives to improve and implement these types of fruit and vegetable harvesters with increasing wages for workers, decreased following the crop migration, and increased frequency of harvest labor shortages. An increase in the use of this type of harvesting could also have major impacts like consolidation and small farms going out of business (Charlton, 2025).

Many assume that with increased use of automation in agriculture, this automation will take jobs away from human workers and decrease the wages for those jobs. However, based on implementing new labor-saving technologies in the past, Hill et al.(2025) believe this is not the case. They show that there are many instances where when a job in agriculture is replaced with technology, there is an increase in the demand for workers in other tasks or in upstream and downstream operations from the farm. This can also be an opportunity for workers as jobs off the farm usually are higher paying and more stable while still allowing them to be involved in the agri-food system (Hill, Charlton, Taylor, 2025).

Skills

Another factor that has been researched in the agricultural job market is the skills that employers look for when hiring. Thomas et al. (2009); Christiaensen et al. (2020) claim that with the economy becoming more and more knowledge-based, workers will have to change the way they think and be technologically capable. Workers cannot just master predetermined chunks of knowledge to be successful. Now, workers will need to have technical, organizational, and labor market knowledge along with systems thinking, collaboration, and experimentation. They say that because of this shift, the education system and extension system are also going to have to shift to help future workers think differently and be successful. Wilson et al. (2019) dive into soft skills versus technical skills in the agriculture job market. It can be debated whether technical skills are more important than soft skills, each having different opinions, although Wilson found employers have begun to see the importance of soft skills and are increasingly looking for soft skills within employees and future employees. They found that more employers would rather have employees with soft skills like leadership, problem-solving, written and oral communication, planning skills, the ability to function under stress, and teamwork. Employers would rather help those students develop technical skills when on the job. They found this to be true in agriculture jobs, and that many students did not have the soft skills employers were looking for. This is a place where undergraduate programs could set up their students for success by implementing programs to develop these soft skills more often. When looking at job listings, interpersonal skills were mentioned on 74% of them, communication on 73%, computer skills on 55%, and critical thinking skills on 41%. Pogorelskaia and Varallyai (2020) agree that new skills will be needed by the next workforce. There will need to be training and outreach programs to help, and some small or medium farms may not be aware of this skill gap.

Therefore, we can see that things like training, gender, and location are influential on the agricultural job market. Labor shortage, specifically with immigrant workers, is part of the push for adoption of innovations on the farm, allowing for a decreased need for the number of workers needed on an operation while also creating new technology-based jobs. But with this upward shift in the use of technology in agriculture, this requires increased technological skills and knowledge for the future workforce, and education systems will have to adapt. There are also concerns with increasing technology involving inequality, environmental impact, and access to resources.

Chapter 3 - Conceptual Model

When individuals search for employment opportunities, they often evaluate job postings based on how well the position aligns with their interests, qualifications, and career goals. One of the most influential factors in this decision-making process is the salary associated with the position. Salary serves as a signal of how employers value the skills, education, and responsibilities required for a particular role. As job seekers compare opportunities, they may consider whether positions requiring technical expertise, manual labor, soft skills, or higher education levels provide greater compensation. At the same time, employers determine salary offerings based on the perceived value that different job attributes contribute to productivity, efficiency, and organizational success.

This study examines how various characteristics of agricultural job postings influence salary outcomes. Specifically, it investigates whether the inclusion of technology-related skills, manual skills, soft skills, education requirements, job type, geographic location, and timing of the postings affects the salary associated with agricultural positions. Understanding these relationships is important because salary information influences both labor market behavior and workforce development decisions. For students and job seekers, identifying which skills and qualifications are associated with higher wages can help guide educational choices, career preparation, and skill development. For employers, understanding how job attributes influence compensation can improve hiring strategies, help attract qualified applicants, and ensure that salary offerings remain competitive within the agricultural labor market.

An additional point of interest is that some job postings do not disclose salary information. In these cases, applicants may place greater emphasis on other characteristics of the position, such as required skills, work responsibilities, location, or advancement opportunities.

Conversely, the absence of salary information may discourage some applicants from pursuing the position altogether. This highlights the importance of understanding how different job attributes contribute to wage determination and labor market signaling.

The conceptual framework for this study centers on salary as the dependent variable, while the independent variables consist of job attributes including technology mentioned, manual skills, soft skills, education requirements, job type, month of posting, and state location. The framework is designed to organize these characteristics and evaluate the extent to which contributes to variation in salary outcomes.

The primary hypothesis of this study is that technology-related skills are positively associated with salary levels in agricultural jobs. As agriculture increasingly adopts advanced technologies such as precision agriculture, automation, and data analytics, positions requiring technological competencies may command higher wages due to increased demand for specialized skills. Manual and soft skills may also influence salary, although the direction of the relationship may vary depending on the nature of the occupation. Manual skills may increase productivity in labor-intensive roles, while soft skills such as communication, teamwork, and leadership may enhance workplace effectiveness and managerial capacity.

An interaction term between manual and soft skills is included to examine whether the value of manual skills depends on the presence of strong soft skills. A positive and statistically significant interaction effect would suggest that manual skills become more valuable when combined with communication and interpersonal abilities, indicating that employers may reward workers who possess both technical labor capabilities and effective collaboration skills.

Education level is expected to positively influence salary outcomes because higher levels of education generally increase human capital, qualifications, and access to specialized positions.

Job type is also expected to affect salary due to differences in labor demand, skill requirements, and compensation structures across agriculture occupations. State variables are included to account for regional wage differences, labor market conditions, and cost-of-living variations. Finally, month variables are incorporated to control for potential seasonal hiring trends and fluctuations in labor demand throughout the year.

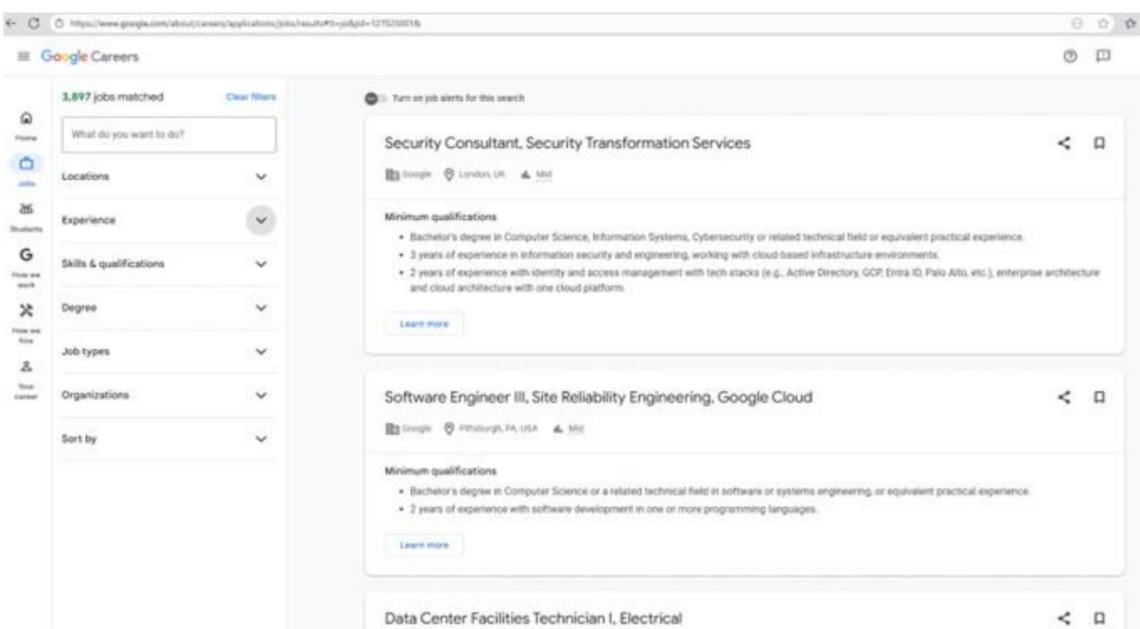
Overall, this conceptual model provides the foundation for the empirical analysis by identifying the factors that may shape salary determination within the agricultural job market. By quantifying the relationship between job attributes and compensation, this study contributes to a better understanding of how skills, technology, education, and labor market conditions influence wages in modern agriculture.

Chapter 4 - Data

This section will present the process of data collection, outputs, and the word vectors that are used in text analysis to create all of our variables from the raw data. It also includes summaries and statistics of the variables.

In Figure 4.1, a program was used to scrape the internet and collect all agricultural job openings from sources like Google Jobs. The scrape has been done once every 4 weeks since October 2023 for the data set used in this research. This study has 182,123 job listings collected over this period. However, when the data is cleaned and the listings that do not mention salary are gotten rid of, this brings us down to about 50,000 listings. This scrape includes all the jobs that are available from Google Jobs, which combines jobs from different company websites as well as job boards, and recruiting platforms. From this information, we have data including the job title, company, location of the job, where it was listed, the job description, when it was posted, and salary, Figure 4.2 shows an example of this raw data. From this raw data we were

Figure 4.1 Example of Google Jobs



able to create dummy variables using text analysis of the job description for the job type, education, skills, location, technology, and the month posted.

Figure 4.2 Example of Scrape Output

title	company_name	location	via	description	posted_at	salary	collection_date
Community Supported Agriculture (CSA) Coordinator (7111)	Fountain Heights Cooperative LLC	Birmingham, AL	via Farm Job List	Job Description: We are seeking a dynamic and motivated individual to join our team as a Community Supported Agriculture (CSA) Coordinator. The CSA Coordinator will play a crucial role in the successful implementation of the "Growing the Fountain Heights CSA" project. This position requires a passionate and experienced professional with a strong background in agriculture, community development... and direct-to-consumer marketing. This person is responsible for managing all administrative tasks related to our 100-member CSA. This individual works closely with farmer participants, and Fountain Heights Farms team members in the office, attends weekly staff meetings, and participates in both big-picture strategizing and daily operational decisions. The CSA (Community Supported Agriculture) Coordinator will be responsible for coordinating and managing all aspects of the CSA program, including member recruitment, marketing, distribution, and customer service. Coordinate all aspects of the CSA program, including member recruitment, retention, and customer service	NA	NA	7/10/24

Creation of Indicator Variables

All of the variables created from the raw data are dummy variables that used text analysis on the job description to pull out words relevant to the variable. In this study, the job description was analyzed and applied to a word vector for our specific dummy variable. Then if any of the words from the vector appear in the job description, that job gets assigned a value of "1." Conversely, if the job description did not yield any of the words from the vector, that job is assigned a "0" value.

For job type, there are dummy variables for jobs including lend/finance, agricultural economics, food science, academic, agriculture education, agriculture sales, agriculture engineering, natural resource, farming, research, agronomy and animal science. For a job to be considered a lending or finance job, the job description had to use any of the following words:

"loan, credit, lender, lending, bank, finance, tax, investment, budget, financial, insurance, account, underwriter, audit or collateral." If any of these words were used, the job is considered a lending or finance job. This same process was followed for all of the job type variables, and the word vectors are in Table 4.1 below.

Table 4.1 Job Type Word Vectors

Job Type	Words Included in the Vector for Text Analysis
Bank/Lending	loan, credit, lender, lending, bank, finance, tax, investmnet, budget, financial, insurance, account, underwriter, audit, collateral
Agricultural Economics	economic, economist, econometric, statistician, risk, commodity, price, pricing, policy specialist, policy analyst
Academic	college, university, professor, dean, adjunct, tenure, chair, post doc, postdoc, faculty, lecture, instructor
Agricultural Education	ag ed, ag teacher, agricultural teacher, ag education, agriculture education, agricultural education, educator, teach, teacher, class, classroom, ffa, 4-h, 4h, ag teacher, teaching, extension educator, future farmers of america, ext agent, extension
Agricultural Engineering	ag systems management, agricultural systmes management, asm, engineer, mechanic, diesel, equipment, service, tech, service manager, maintenance tech, production tech, electrical tech, precision tech, repair, construction, mechan, weld, precision, digital ag, technology
Agricultural Sales	ag sales, agricultural sales, sell, customer, account, commission, sale, seller, buyer, selling, buying
Agronomy	crop advisor, agronomy, agronomist, corn, soybeans, soil, seed, crop, grain, cultivation, greenhouse, irrigation, appraiser, horticulture, fertilizer, pesticide, fungicide, herbicide, applicator, sprayer, botanist
Animal Science	animal, veterinarian, veterinary, sheep, cattle, dairy, swine, pig, pork, beef, livestock, bred, poultry, equestrian, horse, bovine, ranch, farrowing, feedlot, grazing, dairies, milking, egg gatherer, herdsman, herdsperson
Farming	farming, farmhand, planting, plant, harvest, harvester, farm, forage, combine, farmer
Food Science	food science, food production, meat packing, butcher, food distribution, food handling, food processes, food product, meat, produce
Natural Resources	conservation, wildlife, environment, environmental, ecosystem, forest, tree, raw materials, nature, energy, pollution, renewable, fire, climate, natural, sustainable, resources, surveyor, fish, microbiologist, geologist, biologist, biological
Research	research, laboratory, scientist, chemist, lab

Job type was included because salary can vary across different categories and employment sectors. Including job type helps to control for structural differences between occupations within agriculture and improves the accuracy of the estimated relationships between skills and salary.

This method was also used to create education dummy variable for high school, associates, bachelors, master's and PhD degrees. The word vectors are in Table 4.2. Education was included because it is assumed that higher paying jobs require higher education. Including education in these regressions will allow us to distinguish the effects of formal qualifications from the effects of specific skill sets. Roughly 50% of our postings mention a degree level which can be seen in Table 4.8. When creating a job posting a company could include a preferred education level of bachelor's but would still potentially hire a candidate that has a high school education level. Therefore the "1" value for a given education variable indicates what we assume to be the preferred level of education for that job.

Table 4.2 Education Word Vectors

Education	**Words Included in the Vector for Text Analysis**
High School	High school
Associates	Associate's, associate degree, associate's degree
Bachelors	Bachelors, bachelor's degree, bachelor degree
Masters	Masters, master's degree, master degree, grad school, gradschool, graduate degree, advanced degree
PhD	Phd, p.h.d, ph.d, doctorate, doctoral degree

Again, the same process was followed to create a technology dummy variable where if the words "Microsoft, data, programming, coding, technology, Google Suite, digital, computer, software, Excel, Word, PowerPoint, Python, GIS, and drones" were included, that job got the "1" value for the technology dummy variable as seen in Table 4.3. To do further tests in this study an advanced technology dummy variable was created by only including the more advanced technology terms and a low technology variable excluding those advanced terms. Technology was included because digital and technical skills have become increasingly more important across modern labor markets. This variable captures the extent to which technology-related skills contribute to salary variation across agriculture occupations. These three variables are never run in the same regressions. Each of the models we run has three versions: base technology, advanced technology and low technology.

Table 4.3 Technology Word Vectors

Technology	**Words Included in the Vector for Text Analysis**
Technology	Microsoft, data, programming, coding, technology, google suite, digital, computer, software, excel, word, PowerPoint, python, GIS, drones
Advanced Technology	Programming, coding, software, python, GIS, drones
Low Technology	Microsoft, data, technology, google suite, digital, computer, excel, word, PowerPoint

Dummy variables were also created for manual and soft skills. Clearly, many jobs want both manual and soft skills, so an interaction term was also created by taking the manual skills dummy variable times the soft skill dummy variable. Manual and soft skill word vectors can be seen in Table 4.4. Interaction terms were also created for each of the job types with the three types of technology. Therefore, there are three interaction terms for each job. Manual skills were included to account for jobs that require more physical or hands-on labor. This is relevant because compensation for physically intensive jobs can differ dramatically from more knowledge-based occupations. Including manual skills allows the study to examine whether manual labor competencies are associated with lower or higher wage outcomes relative to other skill categories. Soft skills were included because communication, teamwork, leadership, and other interpersonal skills are increasingly valued by employers. This variable helps to evaluate whether interpersonal skills contribute independently to salary levels after controlling for other factors.

Table 4.4 Skills Word Vectors

Skills	Words Included in the Vector for Text Analysis
Manual Skills	Manual, physical, labor, construction, machinery, equipment, tools, welding, driving, forklift, lifting, carry, lift, chores, livestock, tractors
Soft Skills	Communication, teamwork, collaboration, leadership, problem-solving, adaptability, creativity, time management, organization, critical thinking, work ethic

A dummy variable was also created to try to account for experience. Experience could be a big factor on whether or not a job applicant gets paid a higher salary. Here we created a word vector based on the number of years of experience the job posting requested to get more accurate results as opposed to the word "experience". The word vector can be seen in Table 4.5. This was only added into the Heckman selection model.

Table 4.5 Experience Word Vector

Experience	Words Included in the Vector for Text Analysis
Experience	1 year, 2 years, 3 years, 4 years, 5 years, 6 years, 7 years, 8 years, 9 years, 10 years, 1+ years, 2+ years, 3+ years, 4+ years, 5+ years, 6+ years, 7+ years, 8+ years, 9+ years, 10+ years

Fifty state dummy variables were created that looked at the state where the job was located and one dummy variable for being a remote job. State was included to account for geographic variations in labor market conditions, cost of living, and regional wage differences. Salaries may vary substantially across states due to differences in economic development, industry concentration, labor demand, and local wage standards. Including these state-level controls helps to isolate the relationship between worker characteristics and salary from broader regional economic effects. Within the models, remotes were left out to serve as the baseline and comparative variable for state. These summary statistics can be found in appendix A and appendix B.

Twelve-month dummy variables were created that are based on the original posting date of the job. Month was included to control variation in hiring patterns and labor market conditions. Seasonal fluctuations, economic cycles, and changes in employer demand may influence salary postings over time. Including month fixed effects helps reduce bias arising from short term labor market trends during the study period. We chose month variables over year due to the fact that we only have two years worth of data.

We also created interaction terms between each level of technology and soft skills as well as manual skills. These were created to see the interaction between technology and the different types of skills. We would assume that soft skills would interact more with technology than technology and manual skills. These were only used in the Heckman selection model.

There are some caveats to this data that is used. First, the program that is used to scrape the internet for job listings, does not scrape the website Indeed. However, it is assumed that most jobs are cross posted in multiple spots on the internet, therefore if there are missing postings, it is minimal to none. Second, the program pulls out the most popular jobs in the areas. To combat this, there are many points created in each state to get the maximum number of jobs across each state. Finally, it could be agreed that most farming jobs are not posted on the internet. Most of the time, when someone gets a farming job it is filled within the family or heard by word of mouth. However, based on our farming job type dummy, still 30% of our job listings are considered farming jobs.

Summary Statistics

Table 4.6 presents the descriptive statistics regarding salary. It shows the mean, first quarter, median, third quarter, minimum value and maximum value. Table 4.7 shows the descriptive statistics for the rest of the variables for the whole data set and Table 4.8 represents these statistics for only jobs that include salary on their postings. They are all binary variables, so the table shows the count of ones and proportion of ones for each. These statistics provide an overview of the distribution and variation within the dataset prior to regression analysis.

Table 4.6 Salary Summary Statistics

	Salary
Minimum	\$500.00
1^{St} Quarter	\$40,040.00
Median	\$53,040.00
Mean	\$57,685.00
3^{rd} Quarter	\$70,000.00
Maximum	\$151,795.00

Table 4.7 Summary Statistics for Whole Dataset

	Whole Data Set	
Variable	**Count**	**Percentage**
a. Job Type Variables		
Bank/Lending	107010	58.76%
Agricultural Economics	41854	22.98%
Academic	12190	6.69%
Agricultural Education	61927	34.00%
Agricultural Engineering	118245	64.93%
Agricultural Sales	92598	50.84%
Agronomy	103202	56.67%
Animal Science	56795	31.18%
Farming	117178	64.34%
Food Science	31528	17.31%
Natural Resource	115303	63.31%
Research	107839	59.21%
Nondescript job	2186	1.20%
b. Education Variables		
High School	36183	19.87%
Associates	4986	2.74%
Bachelors	29615	16.26%
Masters	18138	9.96%
PhD	11824	6.49%
c. Technology Variables		
Technology	125569	68.95%
Advanced Technology	51211	28.12%
Low Technology	117721	64.64%
d. Skills Variables		
Manual Skills	146166	80.26%
Soft Skills	112293	61.66%
Interaction term	94853	52.08%
e. Month Variables		
January	16252	8.92%
February	15265	8.38%
March	15196	8.34%
April	14773	8.11%
May	15368	8.44%
June	14929	8.20%
July	13869	7.62%
August	14585	8.01%
September	20574	11.30%
October	14936	8.20%
November	9469	5.20%
December	16907	9.28%

The count is the number of times the binary variable was "1"

The percentage is the count number divided by the total number of observations

The total number of observations is 182123

State statistics included in appendix

Table 4.8 Summary Statistics for Postings that Mention Salary

Salary Only Data Set		
Variable	**Count**	**Percentage**
a. Job Type Variables		
Bank/Lending	35365	71.57%
Agricultural Economics	12299	24.89%
Academic	2036	4.12%
Agricultural Education	19630	39.72%
Agricultural Engineering	30222	61.16%
Agricultural Sales	28487	57.65%
Agronomy	23039	46.62%
Animal Science	16943	34.29%
Farming	28969	58.62%
Food Science	9519	19.26%
Natural Resource	32285	65.33%
Research	28198	57.06%
Nondescript job	431	0.87%
b. Education Variables		
High School	10238	20.72%
Associates	2078	4.21%
Bachelors	11736	23.75%
Masters	7424	15.02%
PhD	3970	8.03%
c. Technology Variables		
Technology	39770	80.48%
Advanced Technology	19856	40.18%
Low Technology	37375	75.63%
d. Skills Variables		
Manual Skills	38510	77.93%
Soft Skills	37294	75.47%
Interaction term	30783	62.29%
e. Month Variables		
January	4538	9.18%
February	4179	8.46%
March	3801	7.69%
April	3567	7.22%
May	4312	8.73%
June	3839	7.77%
July	3318	6.71%
August	4775	9.66%
September	6209	12.57%
October	4120	8.34%
November	2315	4.68%
December	4435	8.98%

The count is the number of times the binary variable was "1"

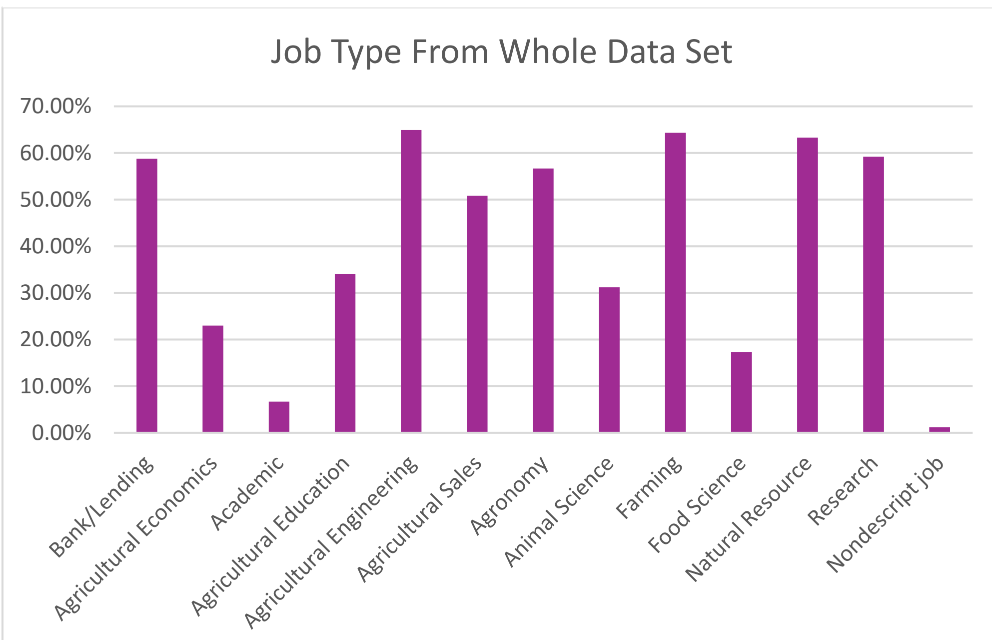
The percentage is the count number divided by the total number of observations

The total number of observations is 49415

State statistics included in appendix

After compiling the data, it is easy to look at the proportions of the different attributes we have included in our data. When looking at all the job types, because jobs can be considered multiple types of jobs, they do not add up to 100%. For instance, an agronomy sales position would be considered both agronomy and agricultural sales. However, we can see that the most prevalent jobs across all the postings are agricultural engineering, farming, and natural science jobs. While this changes slightly if we only look at those postings that include salary, to include lending/finance jobs and exclude farming jobs within the top three. Across both data groups, academic and nondescript jobs are the least prevalent all seen in figure 4.3.

Figure 4.3 Proportion of Job Type from Whole Data Set



In terms of education, when salary is included, a bachelor's degree is the most listed at 23% followed by high school diploma at 20%, but when looking at all our postings, a high school degree is the most listed at 19%. Only about half of our listings have a preferred education listed but when including salary on the listing, this jumps to about 70% of the listings including education. The exact percentages can be seen in Table 4.9.

Table 4.9 Comparison of Education Between Data Sets

	Whole Data Set		**Salary Only Data Set**	
	Count	Percentage	Count	Percentage
High School	36,183	19.87%	10,238	20.72%
Associates	4,986	2.74%	2,078	4.21%
Bachelors	29,615	16.26%	11,736	23.75%
Masters	18,138	9.96%	7,424	15.02%
PhD	11,824	6.49%	3,970	8.03%
Education Listed	100,746	55.32%	35,446	71.73%

The count is the number of times the binary variable was "1". While the percentage is the count number divided by the total number of observations.

For the whole data set the total number of observations is 182,123 and for the salary only data set was 49,415

When looking at our technology variables, technology is present in about 70% of the job postings but this increases to 80% when looking only at the postings that list salary. Advanced technology is only present in 28% of the total postings but this jumps to 40% for postings that list salary. In terms of low technology, it is in about 65% of the job postings and 75% of the salary mentioned postings. Exact numbers can be seen in Table 4.10.

Table 4.10 Comparison of Technology Variables Between Data Sets

	Whole Data Set		**Salary Only Data Set**	
	Count	Percentage	Count	Percentage
Technology	125,569	68.95%	39,770	80.48%
Advanced Technology	51,211	28.12%	19,856	40.18%
Low Technology	117,721	64.64%	37,375	75.63%

The count is the number of times the binary variable was "1". While the percentage is the count number divided by the total number of observations.

For the whole data set the total number of observations is 182,123 and for the salary only data set was 49,415

When salary is listed, manual and soft skills are observed in about three fourths of the listings each individually and 60% together. But interestingly, when looking at all the job postings, manual skills are observed in 80% of the jobs, and soft skills are only observed in 60% of the jobs, about 50% together as seen in Table 4.11.

Table 4.11 Comparison of Skills Between Data Sets

	Whole Data Set		**Salary Only Data Set**	
	Count	Percentage	Count	Percentage
Manual Skills	146,166	80.26%	38,510	77.93%
Soft Skills	112,293	61.66%	37,294	75.47%
Interaction Term	94,853	52.08%	30,783	62.29%

The count is the number of times the binary variable was "1". While the percentage is the count number divided by the total number of observations.

For the whole data set the total number of observations is 182,123 and for the salary only data set was 49,415

Interaction variables were also created between the different levels of technology and soft skills as well as for the technology levels and manuals. These were created to see if there is an interaction been the corresponding type of skill and the varying levels of technology. In Table

4.12 the summary statistics for these interaction terms it can be seen that the base technology with both soft skills and manual skills are the lowest compared to the other levels of technology.

Table 4.12 Comparison of Technology and Skills Interaction Terms Between Data Sets

	Whole Data Set		**Salary Only Data Set**	
	Count	Percentage	Count	Percentage
Technology x Soft Skills	27,457	15.08%	7,314	14.80%
Advanced Technology x Soft Skills	112,293	61.66%	37,294	75.47%
Low Technology x Soft Skills	91,853	50.43%	31,681	64.11%
Technology x Manual Skills	30,111	16.53%	7,837	15.86%
Advanced Technology x Manual Skills	146,166	80.26%	38,510	77.93%
Low Technology x Manual Skills	97,980	53.80%	30,290	61.30%

The count is the number of times the binary variable was “1”. While the percentage is the count number divided by the total number of observations.

For the whole data set the total number of observations is 182,123 and for the salary only data set was 49,415

In Table 4.13 shows the summary statistics for the experience variable that was created. We can see that experience increases from about 22% with the whole data set to 31% in the salary only data set. This could be because job postings that include salary are more complete.

Table 4.13 Comparison of Experience Between Data Sets

	Whole Data Set		**Salary Only Data Set**	
	Count	Percentage	Count	Percentage
Experience	40,979	22.50%	15,330	31.02%

The count is the number of times the binary variable was “1”. While the percentage is the count number divided by the total number of observations.

For the whole data set the total number of observations is 182,123 and for the salary only data set was 49,415

Chapter 5 - Methods

The purpose of this study is to estimate how different skill types of influence salary outcomes. Specifically, this analysis focuses on the relationship between salary and three main categories of skill: manual skills, soft skills, and technology skills. Because skill sets may not influence salary independently, this study also includes an interaction term between manual skills and soft skills to test whether the relationship between manual and soft skills depends on each other.

To address these questions, three econometric models were estimated. First, Ordinary Least Squares (OLS) regression is used to analyze the connection between skill and salary as a continuous variable. Second, an ordered logit model is used when salary is grouped into four different income bands. Third, a Heckman Selection model is used to account for potential sample selection bias if salary is only observed for a subset of job postings. These three models create a more complete analysis of salary determination in job postings while accounting for differences in outcome measurement and possible selection issues.

Econometric Framework

This analysis models salary as a function of multiple skills, demographics, and job-related characteristics. Salary is assumed to depend on manual skills, soft skills, and technology skills, as well as the interaction between manual and soft skills. Control variables are also included to account for additional factors that could influence salary, including state, job type, month, and educational level.

In a general form, this can be expressed as:

$$Salary_i = f(Manual_i, Soft_i, Tech_i, Manual \cdot Soft_i, Controls_i) + \epsilon_i$$

where $Salary_i$ represents the salary for job posting i , the skill variables represent the skills mentioned within each posting, and the control variables account for observable differences between the skill wanted and job characteristics. The error term $\in_i$ captures the unobserved factors affecting salary listed. When applicable, technology is replaced by advanced and low technology variables and run as a separate regression. All models were estimated without an intercept term. This exemption avoids perfect multicollinearity and allows coefficient estimates to be interpreted directly rather than relative to a reference group.

Model 1: Ordinary Least Squares

Ordinary Least Squares regression is used to estimate the relationship between the skill variables and salary when salary is measured as a continuous dependent variable. OLS is often used because it creates straightforward coefficient estimates to interpret as marginal effects.

The OLS model in this study is expressed as:

$$Salary_i = \beta_1 Manual_i + \beta_2 Soft_i + \beta_3 Tech_i + \beta_4 (M \cdot S_i) + \beta_5 State_i + \beta_6 JobType_i + \beta_7 Month_i + \beta_8 Educ_i + \mu_{it} + \in_i$$

where $Salary_i$ represents the salary of the job posting i , $Manual_i$ represents manual skill mentioned, $Soft_i$ represents soft skill mentioned, and $Tech_i$ represents technology mentioned. The interaction term $(M \cdot S_i)$ is included because job postings can include manual and soft skills, so this will test if the relationship between manual skills and salary depends on soft skills. The additional control variables include the state where the job is located, job type, month, and preferred education level. The fixed effects are represented by μ_{it} that is a function of both time t and job posting i. This model was run in R. Again, the technology variable is replaced with advanced and low technology in separate regressions to compare the technology use.

The coefficients of $\beta_1,\ \beta_2,\ \beta_3$ represent the estimated effects of each skill variable and technology on salary when all other variables are held constant. The coefficient of the interaction term β_4 represents whether the effect of manual skills changes as soft skills increase.

Model 2: Ordered Logit Model

In addition to evaluating salary as a continuous outcome, this study also estimates salary using an ordered logit model where salary is organized into income groups. To estimate the ordered logit model, salary was converted into an ordinal dependent variable by grouping job listing salaries into four income bands. The salary bands were constructed to reflect a meaningful wage grouping while keeping the bands relatively balanced in distribution of observations. The four categories of salary were defined as low (less than $40,000), mid ($40,000 to $60,000), upper ($60,000 to $80,000), and high (greater than $80,000). These categories represent common wage thresholds and allow the salary outcomes to be interpreted as ordered levels rather than precise dollar amounts.

Due to the dependent variable being categorical but naturally ordered, an ordered logit model is appropriate for this analysis (Lu, 1999). The ordered logit framework estimates the probability that an observation falls into each salary band based on the explanatory variables including manual skills, soft skills, technology, the interaction between manual and soft, and the control variables for state, job type, month, and education level. The categories that were coded are ascending in order such that higher values represent higher salary groups. The ordered logit model accounts for the ranked nature of the outcome of salary, without assuming equal distances between categories.

The ordered logit model assumes the existence of an unobserved latent variable $Salary_i^*$ which represents the underlying salary potential of job listing i (Lu, 1999). As expressed as:

$$Salary_i^* = \beta_1 Manual_i + \beta_2 Soft_i + \beta_3 Tech_i + \beta_4 (M \cdot S_i) + \beta_5 State_i + \beta_6 JobType_i + \beta_7 Month_i + \beta_8 Educ_i + \mu_{it} + \epsilon_i$$

Coefficients from the ordered logit model do not represent direct dollar value changes in salary. Instead, they indicate whether an independent variable increases or decreases the likelihood of a job listing being present in a higher salary band. This model was run in R. Again, the technology variable is replaced with advanced and low technology in separate regressions to compare the technology use.

Model 3: Heckman Selection Model

Finally, this study analyzes this relationship with a Heckman Selection model. This model is appropriate because of the ability to account for any selection bias that could be present. Only about 25% of our listings include the salary that the job listed will pay. Therefore, this creates a potential for sample selection bias, since job postings that report salary may differ from those that do not. For example, certain job types, states, or education requirements may be more likely to include salary information. If the likelihood of reporting salary is correlated with unobserved factors that also influence salary levels, estimating salary determinants using only listings with observed salary could lead to biased and inconsistent results. It also could be that jobs only want to list the salary when it is "high" to allow the salary to influence potential candidates to apply for the job.

The Heckman Selection model is used here to account for this potential bias. The Heckman model corrects for potential sample bias by jointly modeling the decision for salary to be reported in a job listing and the salary level conditional on salary being observed. This approach is used when the dependent variable is only observed for a non-random subset of the data (Heckman, 1977).

The Heckman Selection model is run in 2 stages. The first stage is the selection stage. Here a probit model is run, where salary is the dependent variable and binary, and all of our normal job variables are the independent variables. A binary variable is created for salary here where salary reporting equals 1 if the listing includes salary information and equals 0 otherwise. This stage selects for when salary is present on the listings. This creates the inverse of Mill's ratio (λ) where it is the decreasing function of the probability salary is selected into the sample (Heckman, 1977). The first equation can be expressed as (Greene, 1993):

$$(1)\ S_i^* = \gamma' w_i + u_i$$

$$(2)\ S_i = 1 \qquad\qquad if\ S_i^* > 0$$

$$(3)\ S_i = 0 \qquad\qquad if\ S_i^* \leq 0$$

$$(4)\ Prob(S_i = 1) = \Phi(\gamma' w_i)$$

$$(5)\ Prob(S_i = 0) = 1 - \Phi(\gamma' w_i)$$

where S_i^* is the latent or unobserved variable representing likelihood that job listing i reports salary, this value is not directly observed, and it represents the true tendency behind the binary decision. Where when $S_i = 1$, the job posting does include salary within the listing. When $S_i = 0$, the job posting omits a salary for the job. γ represents the vector of estimated coefficients that measure the effect of each explanatory variable on salary. w_i is a vector of the independent variables for job listings i. Finally, u_i represents the error term. The error term represents the unobserved factors that influence the latent outcome. The $Prob(S_i = 1)$ is the probability that the outcome is one or the probability that salary is mentioned within the job posting and $Prob(S_i = 0)$ is the probability that salary is not mentioned.

Then the second outcome stage is run. Here salary is again the dependent variable with the same explanatory variables, and the inverse Mills ratio λ is included as an additional regressor to correct for selection bias (Greene, 1993):

$$(1)\ y_i = \beta' x_i + \varepsilon_i, \qquad observed\ only\ if\ S_i = 1$$

$$(2)\ (u_i, \varepsilon_i) \sim bivariate\ normal\ [0, 0, 1, \sigma_\varepsilon, \rho]$$

$$(3)\ E[y_i | S_i = 1] = \beta' x + \rho \sigma_\varepsilon \lambda(\gamma' w)$$

$$(4)\ \hat{\lambda}_i = \frac{\phi(\hat{\gamma}' w_i)}{\Phi(\hat{\gamma}' w_i)}$$

where y_i is the salary reported in the job listing i , $\beta$is the vector of coefficients measuring the marginal effect of the explanatory variables on the outcome variable, and X_i is the vector of explanatory variables affecting the outcome for observation. ε_i is the error term and $S_i = 1$ indicated that the observation i is included in the observed sample.

The Heckman model assumes that the error terms from the selection and outcome equations follow a bivariate normal distribution. Specifically, the selection error term u_i and the outcome error term ε_i are jointly distributed with mean zero, variance normalized to one for the selection equation, outcome variance σ_ε, and correlation coefficient ρ indicate the presence of sample selection bias, suggesting that unobserved factors influencing selection are correlated with the outcome equation error term.

To correct for potential sample selection bias, the Heckman model incorporates the Inverse Mills Ratio, λ_i, into the conditional expectation of the outcome equation. The expected value of y_i conditional on selection, $E[y_i\ |S_i = 1]$, consists of the standard regression component $\beta' x_i$ and a correction term $\rho \sigma_\varepsilon \lambda(\gamma' w_i)$. The function $\lambda(\gamma' w_i)$ represents the Inverse Mills Ratio, which is calculated using the ratio of the standard normal probability density function $\phi(\cdot)$ to the cumulative distribution function $\Phi(\cdot)$. The estimated Inverse Mills Ratio, $\hat{\lambda}_i$, is derived from the first-stage probit estimates and captures the non-random probability of an observation being included in the sample. Including the Inverse Mills Ratio in the outcome equation corrects for bias arising from non-random sample selection. This model was run in R. Again, the technology variable is replaced with advanced and low technology in separate regressions to compare the technology use.

Chapter 6 - Results

This chapter presents the findings from the analysis of agricultural job postings collected through online web scraping methods for this study. The results focus on the relationship between salary and skill categories, including manual skills, soft skills, and technology skills. Findings are presented first through descriptive statistics, followed by regression results from the Ordinary Least Squares (OLS), Ordered Logit, and Heckman Selection models.

Descriptive Results

A total of 182,123 agricultural job postings were collected between October 2023 and October 2025. After cleaning the data and removing observations without salary information, approximately 50,000 postings remain for regression analysis. The reduction in observations highlights the limited frequency with which employers disclose salary information in online job postings.

Descriptive statistics indicate substantial variation across job categories, education requirements, and skill demands. Agricultural engineering, farming, and natural resource occupations represented the most common job types within the full dataset. Among postings that reported salary, lending and finance positions became more prevalent while farming occupations became less common.

Technology-related skills appeared frequently throughout the dataset. Approximately 70% of all job postings included at least one technology-related term, while nearly 80% of postings within salary information referenced technology skills. Advanced technology skills appeared less frequently overall but were more common among higher-paying positions.

Manual skills were identified in approximately 80% of all job postings, while soft skills appeared in roughly 60% of postings. Among salary-reporting jobs, both manual and soft skills were observed in nearly three-fourths of listings. The intersection between manual and soft skills appeared in approximately 60% of salary-reporting jobs, suggesting that many employers seek workers possessing both technical labor capabilities and interpersonal competencies.

Educational requirements also differed across postings. Bachelor's degrees represented the most commonly requested education level among postings with salary information, while high school diplomas were the most common requirement across the complete dataset. Higher education requirements appeared more frequently in postings that disclosed salary information.

Ordinary Least Squares Results

An ordinary least squares (OLS) regression model was estimated to examine the relationship between skill requirements and salary outcomes in agricultural job postings. Salary served as the dependent variable, while the independent variables included measures for technology, manual skills, soft skills, an interaction term between manual and soft skills, state fixed effects, month fixed effects, job type, and education level indicators. The model was designed to isolate the effects of different skill categories on salary while controlling for geographic, temporal, and occupational differences across postings. Table 6.1 presents the results from the OLS regression.

To examine how different levels of technology intensity are associated with salary outcomes, three separate ordinary least squares (OLS) regression models were estimated. Each model is identical except for the key independent variable, which alternates between base technology, advanced technology, and low technology classification. All models control for manual skills, soft skills, the interaction between manual and soft skills, state fixed effects, month fixed effects, job type, and education levels. This structure allows for a direct comparison of how varying levels of technological skill requirements relate to salary outcomes while holding other factors constant.

Across all three specifications, the results indicate that technological classification plays a statistically significant but relatively small role in explaining salary variation. In the baseline model using the general technology variable, the coefficient is negative and statistically significant, suggesting that jobs categorized as technology-related are associated with lower salaries relative to the omitted category. In the advanced technology model, the coefficient remains negative but becomes smaller in magnitude and is only marginally significant, indicating a weaker relationship between advanced technological requirements and salary levels. In contrast, the low technology specification provides a benchmark for understanding how less technical roles compare in wage determination.

Despite differences in the technological variables across the models, the coefficients on manual and soft skills remain consistently positive, large in magnitude, and highly statistically significant in all specifications. This suggests that interpersonal and manual competencies are stronger and more stable predictors of salary than technological classification alone. Additionally, the interaction term between manual and soft skills remains negative and statistically significant across all models, indicating diminishing marginal returns when both skill types are required simultaneously.

Control variables, including state fixed effects, monthly indicators, job type classification, and education levels, remain stable across all three regressions. The models consistently show strong geographic variation in salaries, with states such as California, New York, and Massachusetts exhibiting significantly higher salary levels. Education variables also display a clear monotonic pattern, with higher degree requirements (bachelor's, master's, and PhD) associated with progressively higher salaries.

Overall, the similarity in coefficients across the three specifications suggests that the relationship between skills and salary is robust to different definitions of technological intensity. However, the results also indicate that technology variables alone do not strongly drive salary variation compared to manual and soft skills, which remain the dominant predictors of wage differences in the sample.

Table 6.1 OLS Regression Results

	OLS Models		
	(1)	(2)	(3)
	Base Technology	*Advanced Technology*	*Low Technology*
VARIABLE			
Technology	-846.9*		
	(335.8)		
Advanced Technology		-500.6 ·	
		(279.1)	
Low Technology			-1762.5***
			(307.7)
Manual Skills	5484.3***	5424.1***	5540.6***
	(522.0)	(521.1)	(521.4)
Soft Skills	11033.7***	10734.0***	11378.2***
	(534.5)	(517.1)	(530.2)
Banking/Finance	7993.6***	8024.7***	7985.4***
	(294.2)	(294.3)	(290.9)
Agricultural Economics	5107.9***	5061.4***	5117.2***
	(294.2)	(293.4)	(293.4)
Academic	1278.4*	1240.9*	1340.8*
	(616.3)	(616.3)	(616.2)
Agricultural Education	-1493.0***	-1456.8***	-1454.7***
	(274.7)	(276.4)	(274.7)
Agricultural Engineering	711.3*	677.1*	707.0*
	(289.0)	(288.8)	(288.7)

Agricultural Sales	5546.3***	5417.2***	5778.4***
	(261.5)	(259.2)	(264.9)
Agronomy	547.5*	544.3*	546.4*
	(265.8)	(265.9)	(265.8)
Animal Science	-6253.2***	-6264.0***	-6256.7***
	(275.9)	(276.1)	(275.8)
Farming	837.7**	779.9**	934.2***
	(269.1)	(269.2)	(269.7)
Food Science	-4306.6***	-4311.2***	-4287.7***
	(311.8)	(311.9)	(311.6)
Natural Resources	2914.9***	2918.0***	2942.5***
	(276.0)	(277.8)	(274.9)
Research	4489.9***	4427.0***	4622.9***
	(265.0)	(263.9)	(266.0)
Associates	-7144.5***	-7153.8***	-7042.3***
	(603.1)	(603.6)	(603.0)
Bachelors	1488.1***	1491.7***	1601.0***
	(290.5)	(291.3)	(291.1)
Masters	2035.6***	2103.4***	2032.5***
	(379.4)	(382.0)	(379.3)
PhD	16679.6***	16689.0***	16760.9***
	(483.4)	(484.1)	(483.4)
Month Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Observations	49,415	49,415	49,415
R2	0.8402	0.8402	0.8403

Notes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.01 ‘ ‘ 1

Ordered Logit Results

This section presents results from an ordered logit model estimating the relationship between job characteristics and the likelihood of falling into higher salary bands. The dependent variable is constructed by using salary categories (low, mid, upper and high), meaning that the outcome reflects a ranked ordering of wages rather than a continuous measure. As a result, the ordered logit coefficients are interpreted as changes in the log-odds being in a higher salary category. All specifications include the same set of controls as the OLS models to ensure comparability, with alternative definitions of technology exposure tested across models. Across all ordered logit specifications, none of the coefficients are statistically significant, so the results should be interpreted as directional rather than causal. Table 6.2 presents the ordered logit results.

Across the three technology specifications (base, advanced, low technology), the estimated effects of technology exposure remain small and inconsistent. In general, baseline technology exposure is negative, advanced technology is close to zero or slightly positive, and low technology exposure is negative, though still not statistically significant. Manual and soft skills remain close to zero across specifications, and the interaction term is consistently positive but modest in magnitude. These patterns suggest that the way technology is defined does not meaningfully change the relationship between technology exposure and movement into higher salary bands.

Interpreting these coefficients in the ordered outcome context, positive values indicate higher odds of being in upper salary categories, while negative values indicate a greater likelihood of remaining in lower salary bands. However, because none of the technology variables are statistically significant, there is no strong evidence that technology exposure systematically shifts workers into higher or lower salary categories. The interaction term, while positive across models, is not large enough to suggest meaningful complementarity effects between technology measures.

State level controls are generally negative across all technology classification, indicating that most states are associated with lower odds of being in higher salary bands relative to the omitted reference category of remote jobs. A small number of states, including California, Connecticut, Massachusetts, New Jersey, New York, and West Virginia, consistently show positive coefficients, suggesting relatively stronger wage outcomes in those locations. Job-type controls vary in both directions and magnitude, with no stable pattern emerging across categories, indicating heterogeneity in occupational effects that is not consistently tied to salary rank.

Education remains the strongest and most consistent predictor across all ordered logit models. Relative to the omitted category of high school degrees, associates degrees are strongly negative, indicating substantially lower odds of being in higher salary bands. In contrast, bachelor’s degrees, master’s degrees and PhDs are all positive and increasing in magnitude. This produces a clear and monotonic gradient, where higher educational attainment is strongly associated with movement into higher salary categories.

Overall, the ordered logit results across all specifications are consistent with the broader OLS findings. Technology variables do not exhibit statistically meaningful effects on salary band outcomes regardless of how they are defined. Geographic variation is present but largely negative outside a small subset of states, while education is the dominant and most robust determinant of higher salary categories. These results suggest that wage stratification in the sample is driven primarily by educational attainment rather than differences in occupational technology exposure.

Table 6.2 Ordered Logit Regression Results

	Ordered Logit Models		
	(1)	(2)	(3)
	Base Technology	*Advanced Technology*	*Low Technology*
VARIABLE			

Technology	-0.3502		
	(0.0252)		
Advanced Technology		0.0570	
		(0.0204)	
Low Technology			-0.3292
			(0.0228)
Manual Skills	0.0224	-0.0027	0.0170
	(0.0408)	(0.0408)	(0.0408)
Soft Skills	0.1186	-0.0160	0.1075
	(0.0421)	(0.0412)	(0.0419)
Manual/Soft Interaction	0.0731	0.1050	0.0727
	(0.0465)	(0.0464)	(0.0464)
Banking/Finance	0.6238	0.5966	0.6108
	(0.0221)	(0.0223)	(0.0220)
Agricultural Economics	0.3487	0.3255	0.3351
	(0.0217)	(0.0217)	(0.0217)
Academic	-0.0065	-0.0144	0.0020
	(0.0453)	(0.0453)	(0.0453)
Agricultural Education	-0.1471	-0.1628	-0.1443
	(0.0197)	(0.0199)	(0.0197)
Agricultural Engineering	0.2427	0.2347	0.2344
	(0.0212)	(0.0211)	(0.0212)
Agricultural Sales	0.3453	0.3106	0.3687
	(0.0191)	(0.0189)	(0.0193)
Agronomy	-0.1185	-0.1177	-0.1197
	(0.0196)	(0.0196)	(0.0196)
Animal Science	-0.6592	-0.6521	-0.6568
	(0.0204)	(0.0204)	(0.0204)
Farming	-0.1578	-0.1651	-0.1451
	(0.0197)	(0.0197)	(0.0198)
Food Science	-0.4809	-0.4939	-0.4830
	(0.0206)	(0.0230)	(0.0230)
Natural Resources	0.1495	0.1172	0.1385
	(0.0206)	(0.0208)	(0.0206)
Research	0.2712	0.2489	0.2848
	(0.0195)	(0.0195)	(0.0196)
Associates	-0.8254	-0.8550	-0.8248

	(0.0462)	(0.0462)	(0.0463)
Bachelors	0.0804	0.0537	0.0927
	(0.0211)	(0.0211)	(0.0212)
Masters	0.3750	0.3583	0.3714
	(0.0263)	(0.0264)	(0.0263)
PhD	1.457	1.427	1.466
	(0.0347)	(0.0346)	(0.0347)
Month Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Observations	49,415	49,415	49,415

Notes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.01 ' ' 1

Heckman Selection Results

The inverse Mills ratio was positive and statistically significant in all three models, indicating the presence of selection bias in the observed salary sample and validating the use of the Heckman correction procedure. The inverse Mills ratio ranged from 9.420e+04 to 1.013e+05. These findings suggest that unobserved factors influencing whether salary information was reported were also related to salary levels themselves, supporting the appropriateness of the Heckman modeling framework for this analysis. These findings could also be an indication as to why the technology variables in the OLS and ordered logit models were negative, with an opposite sign than was expected.

Table 6.3 reports the Heckman Selection model estimates. The Heckman Selection model was estimated to account for potential sample selection bias in salary observations across agricultural job postings. Three separate specifications were analyzed using technology, advanced technology, and low technology variables. In each model, the first stage selection equation estimated the likelihood that a job posting included salary information, while the second stage outcome equation estimated salary levels conditional on salary disclosure. Across all three models, manual skills, soft skills, the interaction between manual and soft skills, state fixed effects, month indicators, job type, education level, experience, technology/soft skill interaction and a technology/manual skill interaction were included as explanatory or independent variables.

The first stage selection equations produced relatively consistent patterns across all three specifications. The technology variables were all positive, indicating that positions requiring technological competencies were more likely to report salary information. The coefficient was largest in the advanced technology model (0.265), followed by the base technology model (0.206) and the low technology (0.168). These findings suggest that employers recruiting for technologically intensive positions may be more transparent in wage reporting practices.

Manual skills were consistently negative across all three first stage equations, ranging from -0.348 to -0.389, implying that job emphasizing manual labor were less likely to include salary information. In contrast, soft skills were positive in all specifications, with coefficients of 0.117 in the general technology model, 0.126 in the low technology model and 0.175 in the advanced technology model. The interaction between manual and soft skills was also positive across all models, ranging from 0.234 to 0.271. Together, these findings suggest that occupations requiring balanced technical and interpersonal skills were more likely to disclose compensation information within their postings.

State effects in the selection equations were largely negative relative to the omitted reference of remote jobs, with Arkansas consistently serving as the only state with positive coefficients across all three models. Month indicators also followed nearly identical patterns for each model. Relative to the omitted month of December, all months were negative except for November, which maintained a positive coefficient. These findings suggest that both geographic and seasonal variation is salary disclosure practices within the agricultural labor markets.

Occupational categories in the selection equations were predominately negative across all specifications. However, bank/lending, animal science, and food science jobs consistently displayed positive coefficients, indicating that these job categories were more likely to provide salary information. Education variables were also consistently positive across models. Associate's degree requirements ranged from 0.178 to 0.196, bachelor's degrees ranged from 0.166 to 0.180, master's degrees ranged from 0.208 to 0.259, and PhD requirements ranged from 0.112 to 0.126. These findings suggest that higher education requirements increased the probability of salary disclosure in agricultural job postings.

The second stage outcome equations estimated salary determinants after correcting for sample bias. The technology variables all produced positive salary effects except for in the low technology model, although the magnitude varied substantially across specifications. The advanced technology model generated the largest coefficient (26,659), indicating a substantial wage premium for technologically advanced occupations. The general technology model produced a positive coefficient of 13,243, while the low technology model generated a smaller negative effect of 9,612. These findings suggest that increasing technological intensity is associated with higher compensation in agricultural labor markets, particularly for advanced technological skills.

Manual skills remained strongly negative across all salary equations, with coefficients ranging from approximately -31,206 to -40,121. These results indicate that occupations emphasizing manual labor tend to offer lower salaries. The estimated coefficients for soft skills were 17,733 in the base technology model, 20,719 in the low technology model and 20,422 in the advanced technology model. The interaction between manual and soft skills was also positive across all three classifications, ranging from 15,166 to 25,224. This suggests that workers possessing both manual skills and strong interpersonal or soft skills earn higher salaries than workers possessing only one skill set.

State effects in the outcome equations were again primarily negative relative to the omitted remote category, with Arkansas serving as the only state consistently associated with positive salary effects. Month effects also remained consistent across the three models, as all months were negative compared to December except for November, which maintained a positive coefficient. These results indicate seasonal and geographic differences in agricultural wage levels.

Occupational effects in the salary equations showed that most job categories were associated with lower salaries relative to the omitted category, nondescript jobs. However, banking/lending, agricultural economics, agricultural engineering, agricultural sales and animal science occupations consistently demonstrate positive salary effects across all three models. These occupations may demand higher compensation due to greater specialization, technological requirements or labor market demand.

Education variables generally demonstrated positive relationships with salary, although the magnitudes differed across the different technology models except in the advanced technology model, the coefficient being negative for associates. In the base technology model, associate’s degree requirements increased salary by approximately $31.80, bachelor’s degrees by $9,156, master’s degrees by $11,756, and PhD requirements by $23,186. Similar results were observed in the low technology model, with salary increases of $2,037 for associate’s degrees, $8,714 for bachelor's degrees, $14,263 for master’s degrees, and $22,516 for PhD. The advanced technology model differed somewhat, as associate’s degrees produced a small negative coefficient (-3483), while bachelor’s degrees (6,308), master’s degrees (6,473), and PhD requirements (20,604) remained positive. Overall, these findings suggest that advanced educational attainment is strongly associated with higher salaries, particularly at the graduate and doctoral levels.

Added into this model is a dummy variable for experience. Across all three models, the coefficients are positive. Suggesting that experience of any level does increase the salary that jobs post on their listings. For the base technology model salary increased $12.892, for the low technology model it increased $15,130, while it increased by $10,207 in the advanced technology model.

There were also interactions terms included for technology and soft skills as well as technology and manual skills. These interaction terms allow us to test whether the effect of technology depends on whether a job also requires soft skills or manual skills. Without, the interactions, the model assumes the effect of technology is the same for every job. Technology may be valued differently depending on the type of work being performed. For the base technology model and the soft skills interaction, the coefficient is -15,321, for advanced technology the coefficient is -16,286, and the low technology model is 9,546. These results do not say that soft skills lower salary. Instead, they say that employers appear to place less additional salary value on technology when soft skills are already required. For the technology and manual skills interaction, the coefficients are all positive, base technology being 14,401, advanced technology as 4,475, and low technology being 19,577. These results indicate a sort of complementarity. Instead of technology replacing manual work, jobs requiring both appear to be valued more highly.

Table 6.3 Heckman Selection Regression Results

	Heckman Selection Models 1st Selection Stage		
	(1) *Base Technology*	(2) *Advanced Technology*	(3) *Low Technology*
VARIABLE			
Technology	0.2067***		
	(0.0089)		
Advanced Technology		0.2655***	
		(0.0078)	
Low Technology			0.1685***
			(0.0170)
Manual Skills	-0.3840***	-0.3899***	-0.3483***
	(0.0134)	(0.0134)	(0.0147)
Soft Skills	0.1173***	0.1755***	0.1267***
	(0.0147)	(0.0143)	(0.0183)
Manual/Soft Interaction	0.2716***	0.2343***	0.2354***
	(0.0161)	(0.0160)	(0.0180)
Banking/Finance	0.1820***	0.1733***	0.1920***
	(0.0077)	(0.0077)	(0.0077)
Agricultural Economics	-0.0489***	-0.0433***	-0.0454***
	(0.0082)	(0.0082)	(0.0082)
Academic	-0.4566***	-0.4464***	-0.4745***
	(0.0155)	(0.0155)	(0.1550)
Agricultural Education	-0.0473***	-0.05763***	-0.0432***
	(0.0077)	(0.0077)	(0.0075)
Agricultural Engineering	-0.0233**	-0.0140	-0.0646***
	(0.0085)	(0.0086)	(0.0080)
Agricultural Sales	-0.0205**	0.0173*	-0.0230**
	(0.0074)	(0.0074)	(0.0075)
Agronomy	-0.2249***	-0.2251***	-0.2287***
	(0.0075)	(0.0075)	(0.0075)
Animal Science	0.1027***	0.1063***	0.1028***
	(0.0076)	(0.0076)	(0.0076)
Farming	-0.0946***	-0.0894***	-0.0912***
	(0.0076)	(0.0076)	(0.0076)

Food Science	0.0710***	0.0685***	0.0704***
	(0.0088)	(0.0088)	(0.0088)
Natural Resources	-0.1355***	-0.1517***	-0.1321***
	(0.0077)	(0.0078)	(0.0077)
Research	-0.1401***	-0.1275***	-0.1460***
	(0.0075)	(0.0075)	(0.0075)
Associates	0.1923***	0.1788***	0.1960***
	(0.0197)	(0.0198)	(0.0196)
Bachelors	0.1800***	0.1665***	0.1675***
	(0.0090)	(0.0090)	(0.0090)
Masters	0.2466***	0.2081***	0.2599***
	(0.0115)	(0.0116)	(0.0115)
PhD	0.1266***	0.1120***	0.1185***
	(0.0143)	(0.0144)	(0.0143)
Experience	0.2308***	0.2194***	0.2347***
	(0.0078)	(0.0079)	(0.0078)
Technology/Soft Interaction	-0.2525***	-0.2907***	-0.0225
	(0.0197)	(0.0197)	(0.0159)
Technology/Manual Interaction	0.1166***	0.1769***	0.0216
	(0.0187)	(0.0186)	(0.0181)

	Heckman Selection Models 2nd Outcome Stage		
	(1) *Base Technology*	(2) *Advanced Technology*	(3) *Low Technology*
VARIABLE			
Technology	13243.3**		
	(4401.6)		
Advanced Technology		26659***	
		(4100)	
Low Technology			-9612
			(7901)
Manual Skills	-33458***	-31206***	-40121***
	(8557.7)	(8552)	(9226)
Soft Skills	17733.5**	20422**	20719*

	(6640.9)	(6365)	(8489)
Manual/Soft Interaction	25224.5**	19841*	15166 ·
	(8725.2)	(8523)	(9096)
Banking/Finance	24415.8***	21688***	26682***
	(3808.5)	(3792)	(3878)
Agricultural Economics	16393.1***	16714***	16904***
	(3625.1)	(3605)	(3636)
Academic	-39119.1***	-35558***	-44746***
	(8809.1)	(8717)	(8973)
Agricultural Education	-14024.2***	-15516***	-14211***
	(3379.2)	(3403)	(3392)
Agricultural Engineering	5785.6	6614 ·	1903
	(3705)	(3696)	(3571)
Agricultural Sales	3127.6	6258*	1904
	(3205.3)	(3159)	(3280)
Agronomy	-13239.5**	-11898**	-15187***
	(4033)	(4009)	(4056)
Animal Science	3127.6	3118	3777
	(3534.1)	(3536)	(3546)
Farming	-4224.9	-2784	-4475
	(3534.1)	(3426)	(3458)
Food Science	-7457.5 ·	-8590*	-6819 ·
	(3852.3)	(3842)	(3865)
Natural Resources	-4409.9	-6182	-5532
	(3712.6)	(3794)	(3710)
Research	-4186.9	-2488	-5572
	(3601.8)	(3534)	(3642)
Associates	31.8	-3483	2037
	(7512.5)	(7466)	(7550)
Bachelors	9156.7*	6308	8714*
	(4004.4)	(3932)	(3980)
Masters	11756.1*	6473	14263**
	(5210.8)	(5072)	(5286)
PhD	23186.5***	20604***	22516***
	(5991.4)	(5963)	(5992)
Experience	12892.5***	10207**	15130***
	(3856.2)	(3784)	(3900)

Technology/Soft	-15321	-16286 ·	9546
Interaction	(9551.5)	(9577)	(7510)
	14401.8	4475	19577*
Technology/Manual	(8964.3)	(8946)	(8495)
Interaction			
Month Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Observations	182,123	182,123	182,123
R2	0.0454	0.0454	0.0455
Inverse Mills Ratio	1.013e+05	9.420e+04	1.122e+05

Notes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.01 ‘ ‘ 1

Chapter 7 - Summary/Conclusion

Overall, the results from the OLS, ordered logit and Heckman selection regressions provide consistent evidence that education and skill composition are stronger determinants of salary outcomes in agricultural job postings than technology alone. While the effects of technology differ depending on the model, the broader findings suggest that technological intensity by itself does not fully explain wage variation across agricultural occupations. Instead, salary outcomes are more strongly associated with combinations of manual skills, soft skills and education.

The OLS model demonstrated that technology variables were statistically significant but relatively small in magnitude compared to other explanatory variables. Base technology was associated with lower salaries, while advanced technology produced weaker and less consistent effects. Across all technology classifications, manual and soft skills remained positive, large and highly significant predictors of salary, indicating that agricultural employers continue to place substantial value on workers possessing both practical and interpersonal competencies. The consistently negative interaction term between manual and soft skills in the OLS models suggests diminishing returns when occupations simultaneously demand high levels of both skill types. The technology variable coefficients being negative are not what we would expect. This is potentially due to the selection bias that we correct for with the Heckman selection model.

The ordered logit models largely reinforced these findings. Technology variables remained statistically insignificant across all specifications, indicating little evidence that technology systematically increases the likelihood of falling into higher wage categories. Instead, education emerged as the dominant predictor of movement into upper salary bands. Higher education attainment consistently increased the odds of being in higher wage categories, while lower education levels were associated with substantially lower salary outcomes. Geographic variation was also present, although positive salary effects were concentrated in only a small subset of states. We assume that the results are not significantly significant because of the selection bias, which we correct for with the Heckman selection model.

The Heckman selection models provided additional insight by correcting for potential bias associated with salary disclosure in job postings. The first stage selection equations indicated that technologically intensive positions and jobs requiring stronger soft skills were more likely to disclose salary information, while occupations emphasizing manual labor were less likely to report wages. After accounting for this selection process, the second stage equations revealed stronger positive effects for technology variables, particularly advanced technology, which generated the largest wage premium across the three classifications. These findings suggest that advanced technology positions do command higher salaries once selection bias is considered. These results could also explain why the technology variables are negative in the OLS and ordered logit regressions because of the presence of the selection bias.

Across all three regressions, several patterns remained consistent. First, education levels were one of the strongest and most stable predictors of salary, with bachelor’s, master’s and PhD all associated with higher compensation. Second, manual labor-intensive occupations tended to exhibit lower salary outcomes, while occupations combining technical and soft skills generally received higher compensation. Third, substantial geographic and occupational heterogeneity existed across the agricultural labor market, indicating that salary determination is influenced by regional labor conditions and occupational specialization in addition to skill requirements.

With all of these results taken together, they suggest that agricultural labor markets are increasingly rewarding human capital rather than technological skills alone. While advanced technology skills contribute to higher wages in some contexts, education and broader manual and soft skills appear to play a more central role in determining salary outcomes. The findings, therefore, support the broader conclusion that modernization within agriculture is raising demand for highly educated workers who possess a combination of technical, interpersonal, and specialized occupational skills.

These findings have several important implications for students, job seekers, employers, and agricultural educators. For students preparing to enter the agricultural workforce, the results suggest that investing in education and developing a diverse skill set may provide greater salary benefits than focusing solely on technology-related skills. While technological proficiency remains valuable, particularly in advanced technology occupations, employers appear to place substantial value on candidates who can combine technical knowledge with strong manual and interpersonal skills. Students pursuing agricultural careers may therefore benefit from educational experiences that integrate technical training, communication skills, leadership development, and practical field experience.

This study has several limitations. First, the analysis is based on agricultural job postings collected through Google Jobs, which may not fully represent the agricultural labor market. The scraping process did not capture Indeed postings, and because Google Jobs prioritizes the most relevant or popular listings, some jobs may have been omitted despite scraping multiple locations within each state. In addition, online postings may overrepresent seasonal agricultural positions, such as H-2A jobs that require public advertising, while permanent farm positions are more likely to be filled through family succession, word-of-mouth, or local hiring practices.

Second, only a subset of job postings included salary information, creating the potential for selection bias, although a Heckman selection model was used to address this issue. Third, the binary variables were created using text analysis and depend on the keywords included in the word vectors, meaning some skills or job attributes may not have been captured. Finally, this study assumes that the education level listed in a job posting reflects the employer's preferred qualifications; however, the employers may be willing to hire applicants with higher or lower levels of education than those explicitly stated. Therefore, the education variables represent advertised requirements rather than the full range of qualifications employers may accept.

For job seekers, the results indicate that emphasizing a broad range of competencies may improve labor market outcomes. Individuals who can demonstrate both technical expertise and soft skills such as communication, teamwork, and problem-solving may be better positioned to compete for higher-paying positions. The findings also suggest that educational attainment continues to play a critical role in salary determination, reinforcing the potential economic returns associated with obtaining bachelor's, master's, or doctoral degrees in agricultural fields.

Employers may also benefit from these findings by recognizing that workforce development strategies should extend beyond technological adoption alone. As agricultural operations continue to modernize, organizations may achieve greater productivity and labor market competitiveness by investing in employee education, professional development, and training programs that strengthen both technical and interpersonal competencies. The results suggest that the highest-value employees are not necessarily those with technical skills alone, but rather those who can effectively integrate technical knowledge with communication, management, and problem-solving abilities.

More broadly, these findings contribute to the understanding of how technological change is reshaping agricultural labor markets. While technology continues to influence the nature of agricultural work, the results suggest that technological advancement complements rather than replaces human capital. As the agricultural sector becomes increasingly data-driven and technologically sophisticated, demand for workers who possess advanced education and a balanced combination of technical, manual, and soft skills is likely to continue growing. Policymakers, educational institutions, and industry leaders may therefore need to prioritize workforce development initiatives that prepare future agricultural professionals for the evolving skill requirements of a modern agricultural economy.

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Appendix A - State Summary Statistics for the Whole Dataset

Whole Data Set		
Variable	Count	Percentage
f. States		
AL	2730	1.50%
AK	679	0.37%
AZ	2717	1.49%
AR	2892	1.59%
CA	9574	5.26%
CO	4358	2.39%
CT	1321	0.73%
DL	886	0.49%
FL	3520	1.93%
GA	4292	2.36%
HI	1406	0.77%
ID	4452	2.44%
IL	7273	3.99%
IN	4432	2.43%
IA	6036	3.31%
KS	7782	4.27%
KY	3538	1.94%
LA	3221	1.77%
ME	1545	0.85%
MD	2112	1.16%
MA	2736	1.50%
MI	3208	1.76%
MN	5561	3.05%
MS	2838	1.56%
MO	4412	2.42%
MT	4033	2.21%
NE	5403	2.97%
NV	783	0.43%
NH	822	0.45%
NJ	1520	0.83%
NM	1807	0.99%
NY	7091	3.89%
NC	5037	2.77%
ND	5479	3.01%
OH	2948	1.62%
OK	1445	0.79%
OR	2337	1.28%
PN	3612	1.98%
RI	421	0.23%
SC	2500	1.37%
SD	4437	2.44%
TN	4564	2.51%
TX	9657	5.30%
UT	2036	1.12%
VT	1049	0.58%
VR	5140	2.82%
WA	6590	3.62%
WV	1124	0.62%
WI	4707	2.58%
WY	1620	0.89%
REMOTE	6183	3.39%

The count is the number of times the binary variable was "1"

The percentage is the count number divided by the total number of observations

The total number of observations is 182123

Appendix B - State Summary Statistics for Salary Only

Salary Only Data Set		
Variable	Count	Percentage
f. State Variables		
AL	765	1.55%
AK	202	0.41%
AZ	777	1.57%
AR	710	1.44%
CA	3098	6.27%
CO	2082	4.21%
CT	305	0.62%
DL	231	0.47%
FL	776	1.57%
GA	1049	2.12%
HI	307	0.62%
ID	1760	3.56%
IL	1791	3.62%
IN	1029	2.08%
IA	1165	2.36%
KS	1740	3.52%
KY	874	1.77%
LA	524	1.06%
ME	394	0.80%
MD	551	1.12%
MA	566	1.15%
MI	848	1.72%
MN	1583	3.20%
MS	557	1.13%
MO	1372	2.78%
MT	1944	3.93%
NE	1698	3.44%
NV	294	0.59%
NH	146	0.30%
NJ	252	0.51%
NM	533	1.08%
NY	1831	3.71%
NC	977	1.98%
ND	1054	2.13%
OH	716	1.45%
OK	456	0.92%
OR	819	1.66%
PN	805	1.63%
RI	81	0.16%
SC	663	1.34%
SD	1141	2.31%
TN	980	1.98%
TX	1853	3.75%
UT	1130	2.29%
VT	207	0.42%
VR	1640	3.32%
WA	2513	5.09%
WV	297	0.60%
WI	1193	2.41%
WY	816	1.65%
REMOTE	1314	2.66%

The count is the number of times the binary variable was "1"

The percentage is the count number divided by the total number of observations

The total number of observations is 49415