Mechanization and Farm Profit: Model and Application to Specialty Crops

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I. Introduction

As the economy grows, the concept of healthy dieting is popularized across countries (Gereffi, Lee, and Christian 2009). Specialty crops including fruits, vegetables, and tree nuts, have been gaining popularities and economic value throughout the years. The growing demand incents the U.S. farmers to grow specialty crops and further elevates the total production. In the United States, the production value of fruits and tree nuts increased from $21.2 billion in 2010 to $28.8 billion in 2019 (USDA NASS 2021). The 240,000 specialty crop farms across the U.S. are producing over 350 types of specialty crops for both the domestic and global marketplaces (Congressional Research Service 2019). Some of the main producing states include California, Florida, Michigan, Oregon, and Washington (Gallardo et al. 2018). In addition to the market demand-driven incentives, the policymakers such as the Federal and state governments are also promoting the development of specialty crops via bills and supporting programs. For instance, the 2018 farm bill (Agriculture Improvement Act of 2018, P.L. 115-334), the USDA Agricultural Marketing Service Specialty Crops Program, the 2019 Florida Specialty Crop Block Grant programs, and more. However, even if the specialty crop market has been growing throughout the years, there are still many challenges that the U.S. growers need to face.

Historically, the U.S. agricultural industry has been facing multiple challenges including labor shortage, escalating farm labor wage, extreme weather, pests, and diseases for decades (e.g., Miranda and Vedenov 2001; Hanson, Hendrickson, and Archer 2008; Hertz and Zahniser 2013; Zahniser et al. 2018). Among these difficulties, the labor shortage and escalating labor costs are especially critical for labor-intensive crop growers during the peak harvesting seasons (Bampasidou and Salassi 2019). Specifically, on average, approximately 42% of the variable production expenses for fruits and vegetables are associated with labor costs in the U.S. agricultural industry (Huffman 2012). The percentage is expected to be higher for the crops with fragile surfaces such as strawberries and blueberries because harvesting these crops demands the workers more time and concentration. For instance, Florida strawberry growers spent approximately 44% of their total production cost on labor from 2008 to 2013 (Guan, Wu, and Whidden 2020). It is extremely challenging for the U.S. growers who face severe shrinkage of the farm labor pool and escalating wages to compete with growers from developing countries with ample farm labor supply and low wages (e.g., Guan et al. 2015; Roka and Guan 2018; Bampasidou and Salassi 2019; Zahniser et al. 2018). At the individual farm level, a grower may suffer loss of profit margin or even net loss in seasons when the crop prices are low. In the long term, some U.S. farms, especially the smaller ones, may exit the business and multiple U.S. commodities would lose market shares in both the domestic and global battlegrounds. Due to the geographic proximity and the effects of The North American Free Trade Agreement (NAFTA), U.S. imports from Mexico have been greatly boosted (Suh, Guan, and Khachatryan 2017). Figure 1 shows that US fruits and vegetables exports to Mexico grow slowly while US imports from Mexico grow exponentially throughout the years. The divergent trajectories of the two trends cause the fruits and vegetables trade deficit with Mexico to continue to broaden. The trend is particularly prominent in the fresh tomato industry. U.S. fresh tomato production has sharply declined by 67%, from 39 million CWT in 2000 to just 13 million CWT in 2020, and is in desperate need of technological innovation (USDA NASS 2022). This decline was mainly due to the competition of imports from countries that have ample labor supply and lower labor costs (Huang, Guan, and Hammami 2022).

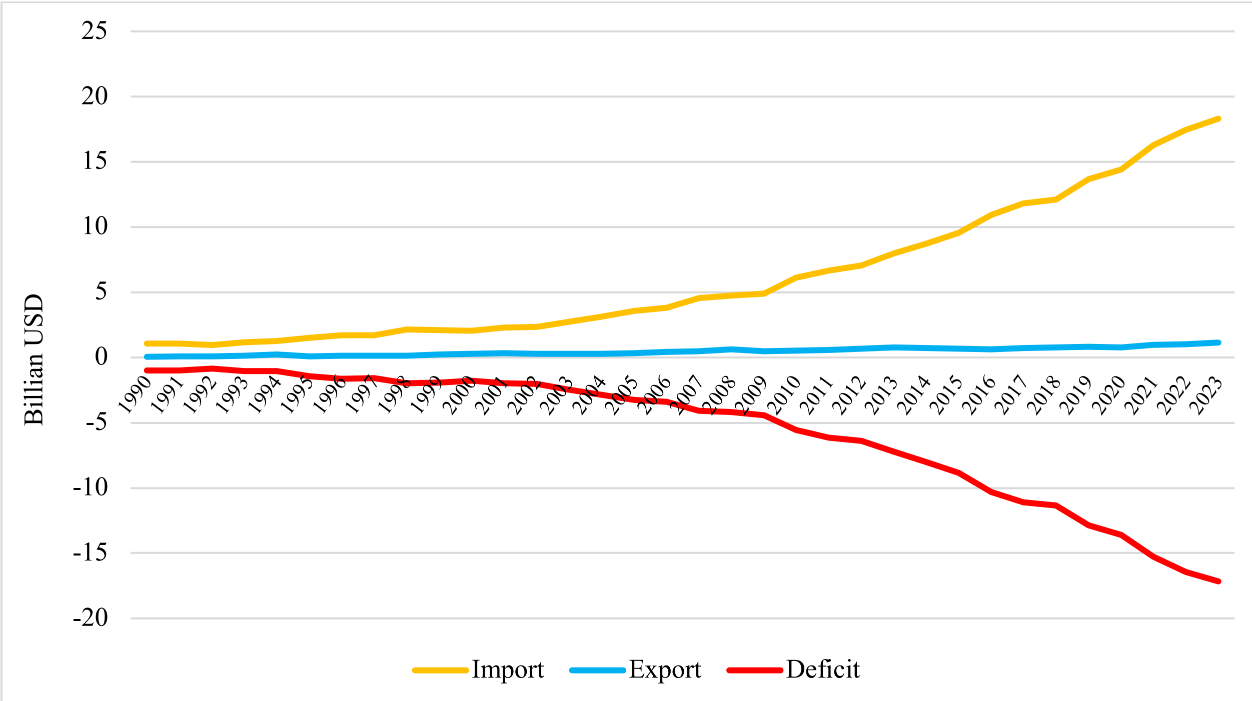

Figure 1. U.S. fresh fruit and vegetables trade with Mexico from 1990 to 2023.

Source: USDA FAS

To encounter these labor challenges and maintain competitiveness against foreign specialty crop producers, mechanical harvesting technology has been proposed as a potential solution for U.S. growers as early as the mid-1950s (Taylor and Charlton 2018). Throughout the years, mechanical harvesting technology has been continuously improving and has further led to broad adoptions in certain industries. For instance, since the 1970s, over 95% of the California tomatoes that are mainly destined for the processing market are harvested by machines (Taylor and Charlton 2018). In 2000, 75% of vegetables and melons from U.S. farms were mechanically harvested (Calvin and Martin 2010). However, these successful cases might not be duplicated easily in delicate fruits such as fresh market tomatoes, blueberries, and strawberries. Machine-harvested fruits may not always meet the quality standards of the fresh markets due to the damages caused by the mechanical harvesters (Takeda et al. 2017). Quality reduction and yield losses were reported as the two important factors that farmers consider when making mechanical harvesting technology adoption decisions (Gallardo et al. 2018). Some growers tend to mechanically harvest only the crops targeting the processing markets that offer lower prices for reduced quality fruits (Gallardo and Zilberman 2016).

Previous studies mainly focus on estimating and comparing single-period profits among different mechanical harvesters (Marra et al. 1989), conducting partial budget analysis (Gallardo and Brady 2015), and assessing the net present value of the capital investment on the mechanical harvesters (Gallardo and Zilberman 2016). However, there is a gap in the literature on the methodology that could be used to model and simulate the interplay of productivity improvement and farm profitability. This research will 1) propose a theoretical framework to demonstrate how mechanical harvester productivity improvement affects farm decisions over time and 2) quantify the impacts of mechanical harvester productivity improvement on farm profitability. We use a representative Florida tomato farm for empirical application and simulate its profit under different productivity improvement and labor wage increase scenarios. The insights from this forward-looking research could inform labor and investment decisions and R&D in agricultural technology, thus influencing strategic planning for agribusinesses.

The next section presents a brief background of the mechanical harvesting technology improvement in the United States. A section introducing the theoretical framework of a representative grower's multi-period profit maximization problem follows. Furthermore, production and operation data of Florida tomato farms are used to quantify these effects in the empirical application section. Scenarios associated with different technology improvement progresses and farm labor wage increase trajectories are considered. Different subsidizing strategies and their potential impacts are assessed and discussed in the policy implication section. The last section concludes this study.

II. Harvesting Technology Productivity Improvement

Specialty crop growers in the United States spend over 40% of their variable production costs on labor (Brady et al. 2016), and the percentage may be even higher for delicate crops. To mitigate the impacts of increasing labor costs, machinery harvesting technology has been proposed as a potential solution to the specialty crop industry as early as the mid-1950s (Taylor and Charlton 2018). There were some successful stories of machinery harvesting technology adoptions. For example, the mechanization of tomatoes in California is one of the most successful cases. A tomato mechanical harvester that could save the growers' harvesting labor usage by roughly 90% was introduced by the University of California-Davis in 1962 (Thompson and Blank 2000). Within four years, 95% of the California tomatoes sold to the processing market were transformed into mechanical harvesting (Thompson and Blank 2000). Thompson and Blank (2000) further indicated that the annual production of processing tomatoes increased from 4 million tons in the 1970s to over 9 million tons in the late 1990s. Moreover, the increased tomato production generated more jobs along the tomato supply chain in California (Taylor and Charlton 2018). Another encouraging example is the mechanization of baby leaf lettuce harvesting. The baby leaf lettuce mechanical harvesting technology was first commercially adopted in the field in the 1990s and its popularity grew rapidly within two decades (Schmitz and

Moss 2015). In the 2000s, 70% to 80% of the baby leaf lettuces across the United States were mechanically harvested (Schmitz and Moss 2015).

These successful cases might not be duplicated easily due to the biological constraints and uncertain hazard events. For instance, despite the success of baby leaf lettuce harvesting, mechanical harvesters have not been widely adopted by the growers of other types of lettuce such as Roman and iceberg because of their ununiform ripening schedules (Schmitz and Moss 2015; Calvin and Martin 2010). Citrus mechanization is a very special case. Prior to the outbreak of Huanglongbing (HLB) known as "citrus greening" in Florida in 2006, more than 36,000 acres of Florida citrus were harvested mechanically using tree shakers (Schmitz and Moss 2015). Unfortunately, HLB affects the infected trees' nutrient absorption and fruit quality, and the growers raised concerns that tree shaking may make their trees more vulnerable to HLB and result in potential long-term yield loss (Schmitz and Moss 2015). As a result, the acreages of mechanically harvested citrus in Florida reduced to less than 9,000 acres in 2013 (Moseley, House, and Roka 2012).

Growers of delicate specialty crops such as fresh market tomatoes, blueberries, and strawberries are also having challenges and difficulties in adopting mechanical harvesting technologies. In the fresh strawberry market, marketable volume and price highly depend on the quality and appearance of the harvested fruits (Klatt et al. 2014). To ensure the quality of the fruits, strawberry growers usually hire hand pickers to harvest the fruits by hand to prevent internal bruises and surface damage. A study about the production cost of Florida strawberries shows that approximately 40% of the total production cost is allocated to labor-related costs (Guan, Wu, and Whidden 2020). So far, the most common semi-mechanical harvesting technology that strawberry growers utilize is the conveyor belts which transport the fruits from the pickers to the trucks or stations (Defterli et al. 2016). However, the main harvesting task, removing the fruits from the branches, is still highly reliant on the hand pickers. In recent years, the researchers who aim to invent robots that perform the “picking” task are getting some promising results, but more improvements in reliability and reductions in maintenance costs are needed before commercialization (Defterli et al. 2016).

Like the strawberries, the marketable volume and price of the fresh market tomatoes are heavily determined by the qualities of the harvested fruits. Fresh market tomato growers usually hire intensive laborers to hand pick the fruits to secure the qualities and longevities. The multi-period decision model proposed in this study takes into consideration the harvesting technology improvement dynamics and farm labor wage growth. The model is applied to Florida fresh market tomato farms.

III. Optimization Framework

The current productivity, in terms of pick efficiency, of mechanical harvesters for most fresh market fruits has not met the standard for being commercially available. However, the productivity of mechanical harvesters is expected to improve steadily over the years due to technological innovation while the costs of hiring laborers are expected to increase due to increasing minimum wages across the country. The productivity of mechanical harvesters is expected to improve over the years and eventually become competitive relative to the efficiency of laborers. In this research, we use a two-step approach to find the minimum required productivity of mechanical harvesters to be commercially viable and the threshold of the productivity improvement rate that could ensure the fresh market fruit farms' profitability under different farm labor wage increase scenarios.

For the first step, an optimization framework is used to solve farmers' weekly optimal decisions in a single season. The weekly optimal farm decisions under two scenarios 1) employing laborers and 2) utilizing mechanical harvesters are solved respectively. The objective function of the single-season multi-week profit maximization problem is as follows:

$$max_{N_{jt},H_{jt}}\left\{E\sum_{t=1}^{T}\left\{(p_t - w_{jt})\theta_{jt}N_{jt}H_{jt}\right\}\right\}$$

where *j* = *l or m* to represent the use of labor or mechanical harvester, p_t is the fruit price, w_{jt} is the per pound piece rate, θ_{jt} is the harvesting efficiency (pounds harvested per hour), N_{jt} is the number of laborers/mechanical harvesters and H_{jt} is the number of working hours for each labor/ mechanical harvester.

The constraints differ depending on whether a farm employs laborers or utilizes mechanical harvesters. When a farmer employs laborers, the objective function is subject to the following constraints: 1) weekly maximum and minimum working hour limit: $Limit_l^{min} \leq H_{lt} \leq Limit_l^{max}\ \forall\ t$, 2) yield bound: $\theta_{lt}N_{lt}H_{lt} \leq y_t A\ \forall\ t$, and 3) the number of workers remains the same throughout the same season: $N_{lt} = N_{l1}\ \forall\ t$. When a farmer utilizes mechanical harvesters, the objective function is subject to the following constraints: 1) weekly maximum hour limit: $H_{mt} \leq Limit_m^{max}\ \forall\ t$, 2) yield bound: $\theta_{mt}N_{mt}H_{mt} \leq y_t A\ \forall\ t$, and 3) the number of mechanical harvesters remains the same throughout the same season: $N_{mt} = N_{m1}\ \forall\ t$.

In the first step, for farmers who employ laborers, we find their optimal weekly decisions in the number of laborers employed (N_{lt}), the number of working hours assigned to each laborer (H_{lt}), and their single-season total profits. For farmers who utilize mechanical harvesters, we find their optimal weekly decisions in the number of mechanical harvesters utilized (N_{mt}) and the number of operating hours of each mechanical harvester (H_{mt}), and their single-season total profits.

In the second step, we create scenarios that show various trends in labor wages and improvements in mechanical harvester productivity for upcoming years. Next, we adjust the piece rate for labor and the picking efficiency of mechanical harvesters for each of these future years according to the specified trends. Finally, farmers redo their optimal decision-making process from step 1 for each of these future years. In particular, farmers who employ laborers (utilize mechanical harvesters) make weekly decisions by choosing the optimal number of laborers employed (mechanical harvesters utilized) and the optimal number of working hours assigned to each laborer (mechanical harvester).

After farmers have made decisions for all upcoming years, we analyze the outcomes of farms using laborers versus those employing mechanical harvesters. This comparison helps us determine, under different wage increase and harvesting technology productivity improvement scenarios, the minimum productivity threshold for mechanical harvesters to be economically feasible (or more profitable than laborers) and the rate of productivity improvement needed to retain the profitability of fresh market fruit farms.

IV. Empirical Analysis

For empirical analysis in this study, the optimization framework is applied to a 500-acre representative Florida fresh market tomato farm operating in a perfectly competitive market, subject to operational and market constraints. The representative farm's optimal decisions and outcomes will be simulated. When conducting a numerical simulation, assumptions are made to reduce the complexity of the decision models. One of the strongest assumptions is that the presented profit maximization problem models a deterministic process even though farm labor planning is inherently stochastic because of the uncertainties and randomness of the yield waves. To relax this strong assumption, following earlier studies (e.g., Wishon et al. 2015), we define the necessary coefficients and apply the Monte-Carlo Method to establish the stochastic process of the yield waves and price movements, and we solve the model to maximize the expected harvesting profit.

Yield and price simulations

The fruit development features growth waves that the yield continues to increase until it reaches the peak and subsequently declines (Wu, Guan, and Whitaker 2015). This wave pattern of yield of tomatoes can be formalized with a quadratic specification. Weekly field trial data of Florida tomatoes in the Fall from 2011 to 2017 are used. These experimental trials used standard commercial production practices (e.g., cultivars, fertilization, pest management, etc.). We estimate the coefficients and standard errors using the trial data, and these parameters are used to simulate tomato yield from harvest 1 to harvest t. In this study, we follow the most common practice of Florida tomato farms where each tomato plant is usually harvested three times and set $t = 3$. Figure 2 shows the average three-harvest yield per acre from 1000 simulations.

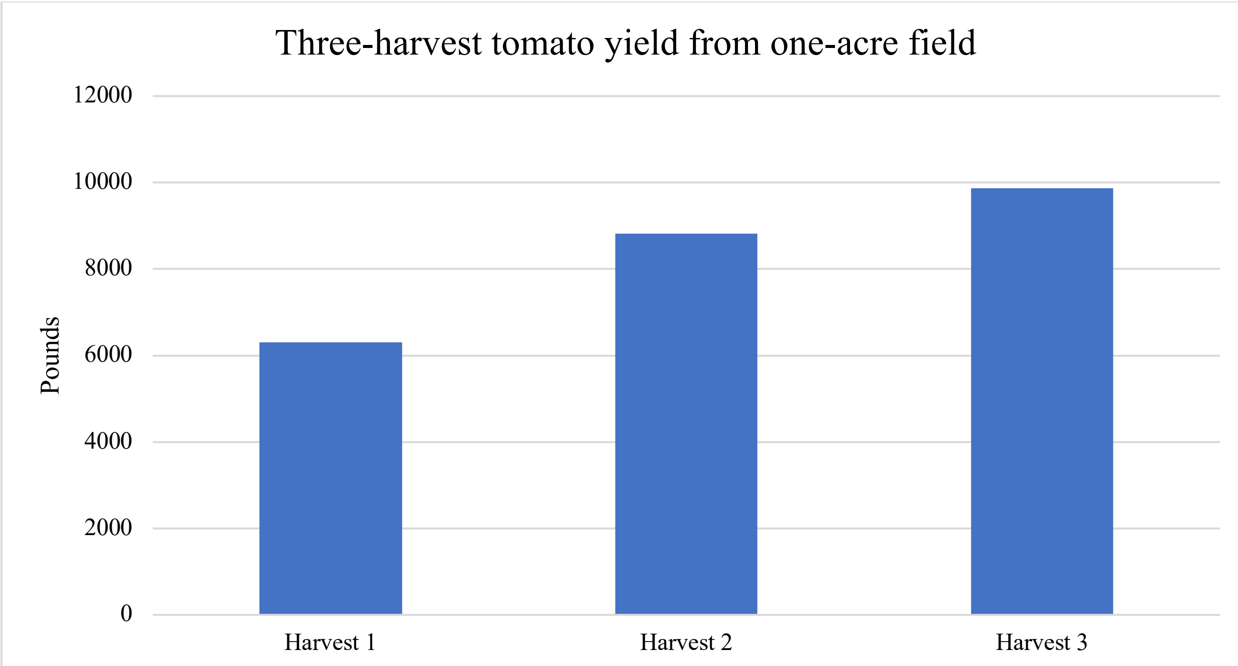

Figure 2. Three-harvest tomato yield from 1-acre field

To guarantee stable weekly tomato yield, growers usually divide entire farmland into multiple fields and plant only one field weekly in a staggered planting schedule. Using a Florida tomato farm with a 10-week planting season and a 12-week harvest season as an example, its entire farmland is divided into ten fields, and one field is planted one week apart throughout a 10-week planting season. Since each field will be harvested three times, there will be one field available for harvest in the first week, two fields available for harvest in the second week, three fields available for harvest starting from the third to the tenth week, two fields available for harvest in the 11th week, and one field available for harvest in the 12th week. By stacking three-harvest yields one week apart ten times, a 12-week yield curve that represents the yield pattern of commercial farms can be derived. The yield of the 11th and 12th week in the 12-week yield curve is the yield of the second and third harvest of the 10th three-harvest yield wave. Figure 3 presents the average weekly tomato 12-week yield from 1000 simulations.

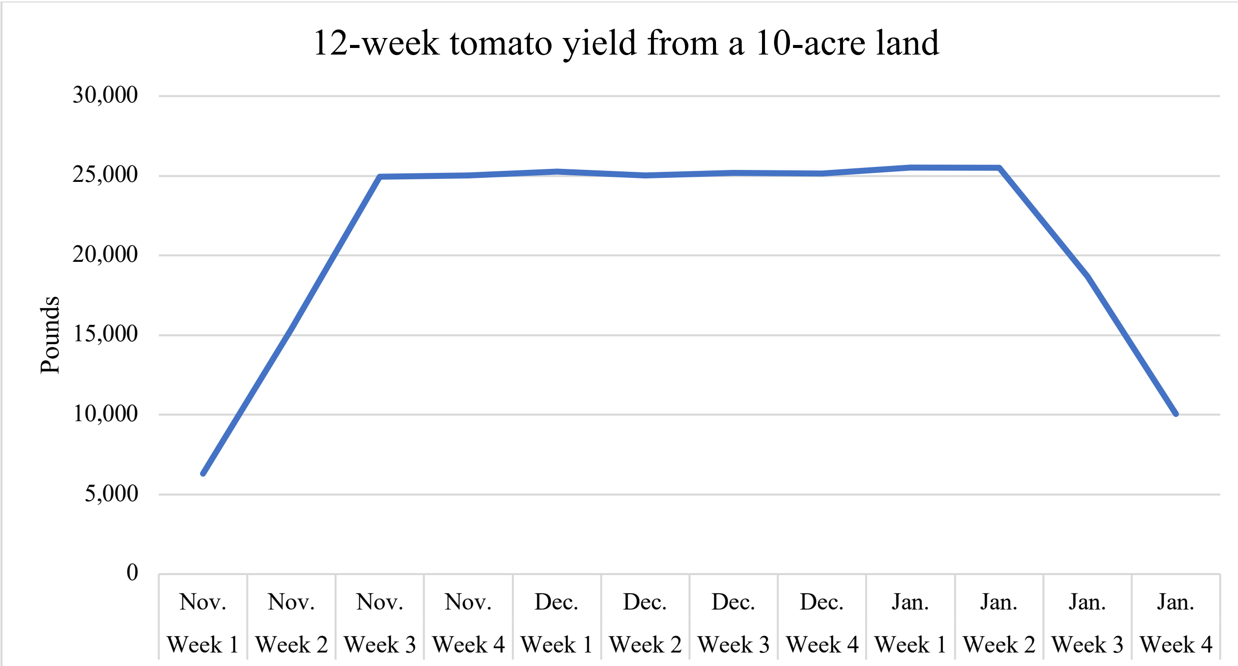

Figure 3. 12-week tomato yield from a 10-acre land

An adaptive approach is used to characterize the random tomato price. The adaptive formulation for determining price dynamics has been employed and suggested by previous studies (e.g., Chavas and Holt 1996). The 2011 to 2017 weekly average shipping point tomato prices (adjusted to the 2021/2022 season level) in Florida are modeled using the adaptive formulation. The regression results, coefficient estimates, and standard errors are then used as the parameters in the price simulations. Since the harvest season of Florida tomatoes in Fall is 12 weeks from November to January, tomato prices of 12 weeks (t=12) are simulated. The average 12-week price curve from 1000 simulations is presented in Figure 4.

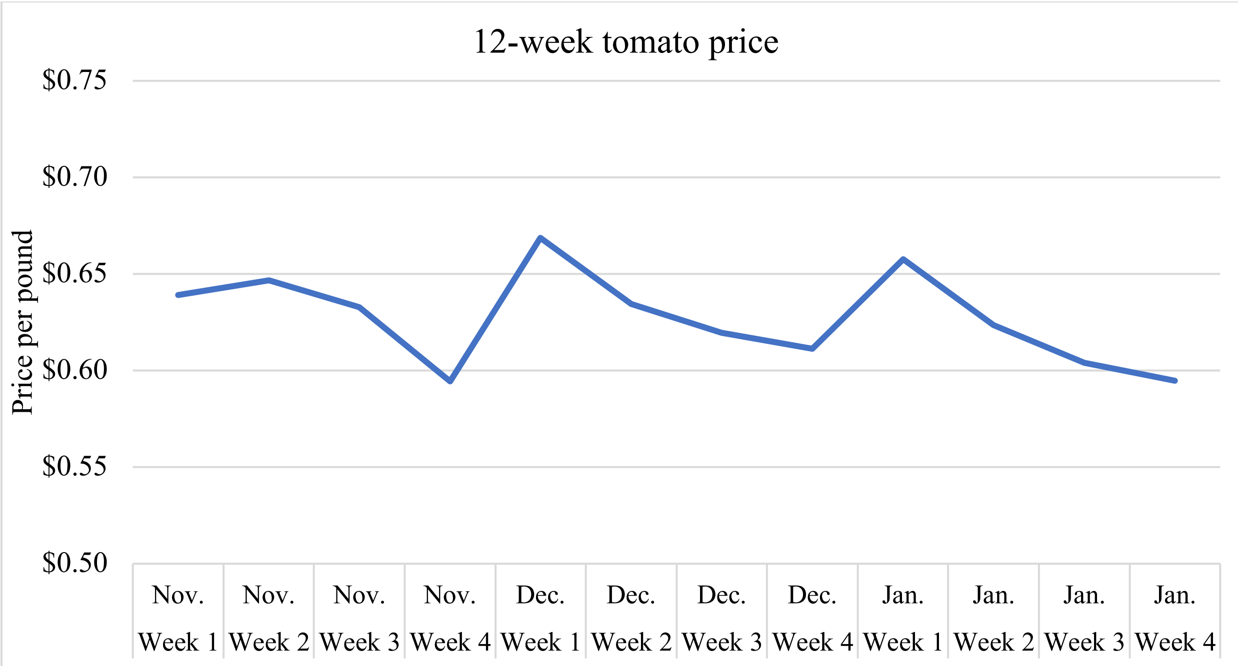

Figure 4. 12-week tomato price

Efficiency and wage parameters

In the tomato industry, laborers are usually paid by a piece rate for each bucket they pick, and each bucket holds approximately 30 pounds of tomatoes. Hence, a worker's hourly wage is the product of the piece rate (per bucket) and the picking efficiency (the number of buckets of tomatoes harvested in an hour). A harvest timing study for conventional tomato harvest in southwest Florida was conducted by Guan, Wu, and Sargent (2018). The average efficiency and piece rate reported in the study are adopted in our simulations for the main discussion, specifically, the picking efficiency of 24 buckets per hour and the average piece rate of 70 cents per bucket are used for the initial year (year 0). For the mechanical harvesters, the picking efficiency of 4.8 buckets per hour and the average piece rate of 3.5 dollars per bucket are used for the initial year (year 0).

Preliminary Results

Our preliminary findings from the farm optimal decision simulation under 10,000 yield-price scenarios show that the speed of productivity improvement relative to wage escalation will determine farm profitability. The harvesting profit threshold is calculated as the total production and operation cost minus the harvesting labor cost. Following the Florida tomato enterprise budget suggested by Wade et al. (2020), after adjusting for inflations, the harvesting profit threshold for the 500-acre representative farm in 2022 is $5,414,150. In other words, to avoid suffering from a net loss, the annual harvesting return of the farm, calculated as the total sales minus total harvesting labor cost, needs to exceed $5,414,150.

There are two assumptions made for scenario 1 which is the most optimistic situation. First, the wage for harvesting labor is assumed to remain constant for the initial four years until Florida's state minimum wage ramps up to $15 as per the scheduled increase, surpassing the 2022 average hourly wage for farm laborers in Florida, which was at $14.28. Beyond the fourth year, the wage is assumed to mirror the average annual salary hike of 3.8% seen across the United States in 2022. Second, the harvesting profit threshold remains constant over time, implying that costs other than harvesting labor are counterbalanced by the rise in future fresh market tomato prices. Despite this optimistic situation, the representative farm is still projected to incur a net loss (where total production costs exceed total harvesting return) starting from year 19. To avert this loss, the cost of picking per pound of tomatoes must decrease by 12% annually.

In the second scenario, while the assumption regarding the harvesting profit threshold remains unchanged, there is a modification in the first assumption concerning the wage for harvesting labor. Specifically, we assume that the farm labor wage will increase by 3.8% annually, aligning with the 2022 U.S. average salary increase, starting in year 1. In this semioptimistic setting, the farm will encounter viability challenges and start suffering from net losses by year 14, which is five years earlier than projected in scenario 1. To avert this outcome, the cost of picking per pound of tomatoes must decrease by 14% annually.

In the final scenario, we not only anticipate a 3.8% annual increase in farm labor wages but also expect all other labor-related costs, including overhead and management salaries, starting from year 1. In this most realistic scenario, the farm will begin experiencing net losses by year 6 and confront survival challenges in the long run. To counter this, the cost of picking per pound of tomatoes must decrease by 50% annually. Regrettably, even with such a significant boost in productivity, the farm will suffer from net loss again in year 13. This underscores the imperative and significance of innovating other production components.

V. Conclusion

Challenges such as labor shortages, rising wages, and competition from countries with lower labor costs threaten the viability of U.S. specialty crop producers. To address these challenges, mechanical harvesting technology has been proposed, but its adoption poses quality and yield concerns. This research aims to contribute to literature and policy discussions by explaining the interplay between technology productivity improvement and farm profitability. An optimization framework to model farmers' optimal decisions regarding the uses of labor and mechanical harvesters is proposed. We use Florida tomato farms for empirical application. The findings from our simulations reveal that the pace of productivity improvement relative to wage escalation significantly influences farm decisions, profit, and long-term viability. Three scenarios were examined, ranging from optimistic to realistic. In the most optimistic scenario, despite favorable assumptions, the farm still faces net losses after a considerable period, necessitating a substantial annual decrease in mechanical harvesting costs. As the scenarios progress towards reality, with increasing wage increments and broader cost considerations, the challenges intensify, leading to earlier projections of viability challenges and financial losses. Notably, even with significant productivity improvements, the farm's profitability and survival are precarious, emphasizing the need for innovation across all production components.

We will further simulate farm decisions and outcomes when productivity improvement follows more complex, stochastic processes. These efforts aim to provide more comprehensive answers to questions, such as the longevity of a farm or specific agricultural sector in the absence of new technology and the necessary pace of productivity improvement to sustain the industry. It is worth noting that this framework can be extended to firms beyond the agricultural sector.

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