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Economic Analysis of Dynamic Controlled Atmosphere Storage for Organic Apples

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Abstract. **Dynamic controlled atmosphere (DCA) storage offers potential economic advantage for organic apple storage, but quantifying these benefits requires accounting for packout uncertainty, seasonal price dynamics, environmental, and location-specific heterogeneity. We developed an integrated empirical simulation that links multiyear storage trials with Monte Carlo revenue modeling to quantify DCA performance relative to controlled atmosphere and regular atmosphere storage. Storage experiments evaluated quality retention or packouts across storage durations and were represented by beta-distributions. A three-stage least squares model identified seasonal price patterns and key determinants of organic apple prices, producing monthly price predictions. Predicted prices were combined with simulated packouts to estimate by cultivar, storage length, and orchard the probability that DCA is revenue superior. Economic outcomes were cultivar, year, and site specific. For organic 'Gala' (*Malus domestica*), the probability that DCA dominates increased from 37.6% in Spring 2022 to 91.8% in Summer 2024, with median revenue advantages for DCA reaching $170,488 per storage room at peak. For 'Honeycrisp', orchard-level heterogeneity was pronounced. Orchard 1 achieved 100% DCA dominance in Spring 2024, whereas 'Honeycrisp' orchard 2 showed variable performance (high of 77.0% to 78.6% in Summer 2022 and Summer 2023). Weather-sensitivity analysis indicated location-specific responses. Elevated harvest temperatures slightly reduced DCA dominance for 'Gala' but sharply reduced it for 'Honeycrisp' (−26.1 percentage points on average). These findings indicate that DCA adoption should be tailored to cultivar, storage duration, and local environmental conditions. The framework provides probabilistic decision support for adoption and timing of DCA in organic apple supply chains by integrating storage performance, price seasonality, and packout uncertainty.**

Apples (*Malus domestica*) are the second most consumed fruit in the United States, with an annual per capita consumption of ~17.2 kg in 2021 (US Department of Agriculture, Economic Research Service 2025a). They provide critical nutritional benefits through their rich fiber, antioxidants, and polyphenolic compounds, which have been associated with lower risks of chronic diseases such as cardiovascular diseases and certain cancers (Hyson 2011; Markosyan et al. 2009). Beyond health, apples play a vital economic role, generating around $4 billion annually in farm gate value and directly and indirectly supporting tens of thousands of rural jobs across the United States (US Apple Association 2022). The major (in volume) apple-producing states, including Washington, New York, and Michigan, particularly benefit from this industry through extensive economic activity and employment creation (Schmit et al. 2018; US Department of Agriculture, National Agricultural Statistics Service 2024).

Consumer demand for organic apples has risen significantly as part of broader growth in the organic food sector, with fresh fruits and vegetables accounting for 40% of US organic food sales in 2021, incentivizing farmers to expand organic production (US Department of Agriculture, Economic Research Service 2025b). Based on trends, organic apples in Washington State account for a significant portion of the US organic apple market, with premiums in 2016 reaching up to 86% at the farmgate level and about 60% at retail compared with conventional apples. This market segment has shown steady growth, providing growers with opportunities to diversify and capitalize on higher pricing (Granatstein and Kirby 2021). Thus, organic production can effectively mitigate market volatility and stabilize grower incomes.

Despite the limited harvest window in the United States from August to November, advanced storage technologies, particularly controlled atmosphere (CA) storage, enable the availability of apples throughout the year. CA storage slows fruit ripening by maintaining low oxygen (1% to 3%) and elevated carbon dioxide (0.5% to 2.5%), extending apple shelf life significantly (Thompson et al. 2018). Organic apples are subject to strict regulations that limit the use of synthetic postharvest treatments such as 1-methylcyclopropene, which can increase susceptibility to storage disorders such as senescence-related internal browning and superficial scald. The inability to apply these treatments to organically produced apples requires careful management of storage conditions to mitigate quality degradation and economic losses (Prange and Wright 2023).

Storage disorders vary significantly by apple cultivar. In this study, we focus on two cultivars with distinct responses to storage regimes: 'Gala' and 'Honeycrisp'. Organic 'Gala' apples, the highest volume cultivar produced in Washington and the United States, are particularly prone to loss of firmness and senescence-related internal browning in long-term storage (Argenta et al. 2022). In contrast, organic 'Honeycrisp' apples, recognized for their premium market position due to their distinctive crisp texture, are highly susceptible to disorders such as bitter pit (Islam et al. 2022). Other storage disorders, including soft scald and soggy breakdown in 'Honeycrisp', also pose economic risks by potentially reducing the marketable yield of these apples (Robinson et al. 2024).

Given these considerations, dynamic controlled atmosphere (DCA) was developed to address several inherent issues to storage of fresh apples among other fresh produce (Deuchande et al. 2016; Thewes et al. 2024). DCA adjusts oxygen levels dynamically throughout the storage period by monitoring fruit stress signals in response to low oxygen stress (Thewes et al. 2024). This allows for further reduction in respiration and ethylene production compared with standard CA storage, which delays ripening and senescence (Thewes et al. 2024; Wright et al. 2015). Several DCA methods, including chlorophyll fluorescence and respiratory quotient techniques, have been effective in managing low oxygen levels while also demonstrating the ability to effectively lower metabolic rates and protect against storage disorders such as internal browning (Büchele et al. 2023; DeEll et al. 2022; Deuchande et al. 2016; Thewes et al. 2024).

Although technological advances in DCA have progressed, research evaluating its economic impact remains limited. Existing studies on the technology focus mainly on physiological results, thus creating a gap in providing a comprehensive assessment of the economic implications associated with adopting the technology. On a positive note, ongoing economic analyses in the United States are already aiming to quantify cost–benefit trade-offs, further informing adoption decisions (US Department of Agriculture, National Institute of Food and Agriculture 2025).

Our approach integrates fruit physiology metrics with economic data, using Monte Carlo simulations to capture the economic implications of adopting DCA storage under uncertainty. A single commercial DCA system was used across rooms, with O_2 levels 0.1% to 0.2% O_2 above the low oxygen limit (LOL) determined using the respiratory quotient (RQ) value (0.7 to 0.8).

The study's contributions are 3-fold. First, it addresses the research gap by conducting an economic analysis of the implementation of DCA in apple storage. Second, we introduce a Monte Carlo simulation framework that quantifies the probability of DCA economic dominance over other storage technologies using beta-distributed packout rates, providing growers with risk-adjusted decision metrics rather than point estimates. Through an evaluation of three different storage technologies for organic 'Gala' and 'Honeycrisp' apples across orchard locations and across years, the study identifies the influence of cultivar, microenvironments, year, and orchard site on the efficacy of the storage protocol. Therefore, the study offers practical guidance for growers seeking to optimize storage strategies tailored to specific environmental conditions and risk tolerance.

Materials and Methods

This study investigates the economic impact of using DCA technology for maintaining the quality of organic apples over a range of storage durations. The analysis comprises three distinct components. First, we conduct a probabilistic analysis of apple quality, assessed by the proportion of apples deemed suitable for sale without exhibiting disorders or decay, under regular atmosphere (RA), CA, and DCA storage conditions. Second, we construct an econometric model to forecast monthly apple prices, incorporating seasonal variations and pertinent price determinants. Third, we employ Monte Carlo simulations to account for storage outcome uncertainty. These predictions, in conjunction with the quality outcomes, facilitate the estimation of the revenue implications of each storage technology across different storage durations.

Assessment of apple quality storage technologies and durations. The packout trajectories (defined as the percentage of marketable fruit) used in the economic analysis were derived from controlled storage trials conducted at the postharvest laboratory of the Washington State University (WSU) Tree Fruit Research and Extension Center. The trials evaluated organic 'Gala' apples from a single commercial orchard (2022–24) and organic 'Honeycrisp' apples from two commercial orchards (2022–24). Assessments were made at ~3 months + 7 d, 6 months + 7 d, and 9 months + 7 d after harvest, followed by 7 d at ambient conditions. We present orchard-year heterogeneity via distributional displays using median/interquartile ranges (IQRs), rather than pooling across conditions.

The postharvest data used in the first stage were collected through controlled storage experiments conducted at WSU. The primary hypothesis guiding this research is that the economic advantages derived from implementing DCA technology become increasingly pronounced as storage durations lengthen. Extending the preservation capability allows growers and storage facility operators to strategically align apple supply with year-round market demand, mitigating the limitations of the inherently short harvest season.

The experimental data set comprises quality evaluations for organic fruit: 'Gala' and 'Honeycrisp', subjected to RA (3 °C for 'Honeycrisp'; 0 to 1 °C for 'Gala'), CA (3% O_2, 0.5% CO_2 for 'Honeycrisp'; 2% O_2, 0.5% CO_2 for 'Gala'), and DCA storage conditions. For DCA storage, CO_2 levels remained static and similar to CA, and O_2 dynamically changed throughout storage based on the LOL determined by RQ (Labpods; Storage Control Systems, Inc., Union Gap, WA, USA) (Storage Control Systems 2021). DCA conditions for 'Honeycrisp' were 2.0% to 0.3% O_2 for orchard 1 and 2.0% to 0.6% for orchard 2 and for 'Gala' were 1.7% to 0.3% O_2. Apple quality was evaluated using three indicators: (1) the percentage of marketable fruit (apples free from both physiological disorders and microbial decay), (2) the percentage of apples exhibiting physiological disorders, and (3) the percentage of apples showing microbial decay. Note that for the economic analysis, we focus solely on marketable fruit percentage, as this directly determines revenue. The specific disorder types do not affect fresh market prices in Washington as there is no market for substandard apples in the state. Evaluations were conducted periodically, ranging from a minimum storage duration of about 3 months (3 months + 1 and 7 d) to a maximum exceeding 9 months (9 months + 1 and 7 d).

Organic 'Honeycrisp' apples were evaluated over three consecutive years (2022–23, 2023–24, and 2024–25) using samples from two commercial orchard locations: 'Honeycrisp' orchard 1 in Othello, WA (Adams County) and 'Honeycrisp' orchard 2 in Quincy, WA (Grant County). Similarly, quality data for organic 'Gala' apples were collected for the same years as 'Honeycrisp' but from a single orchard, 'Gala' orchard 1 in Quincy, WA (Grant County).

Our analysis focuses on three storage intervals: short-term (3 months + 1 and 7 d), medium-term (6 months + 1 and 7 d), and long-term (9 months + 1 and 7 d), aligning with periods of apple availability and changing prices. At each interval, the quality indicators were systematically recorded. Rather than presenting simple averages, we display the full distribution of outcomes across orchard-year combinations to capture heterogeneity in storage responses.

Modeling marketable-fruit proportions (packout). Packout is a bounded proportion between 0 and 1; we model its uncertainty with the beta family distribution, which is designed for continuous proportions and can flexibly represent symmetric and skewed distributions (Douma and Weedon 2019; Ferrari and Cribari-Neto 2004; Warton and Hui 2011). We fit a separate beta distribution for each orchard-year × cultivar × storage technology × release month combination "cell" (see Supplemental Appendix A1).

To obtain stable estimates when a cell has few replicates or near-zero variance, we used a two-stage procedure. First, we initialized the two beta shape parameters using the standard mean-precision reparameterization derived from the beta mean and variance expressions (Johnson et al. 1995; National Institute of Standards and Technology/SEMATECH 2012). To avoid extreme or degenerate starts in sparse cells, we constrain the initial beta precision or concentration parameter κ (defined in Supplemental Appendix A1) to a moderate, data-informed range. In detail, we exclude starting values that imply implausibly low precision or near-deterministic concentration, which may arise in sparse or low-variance settings. This regularization leaves the likelihood unchanged but prevents overconfident initializations (Ferrari and Cribari-Neto 2004). This is consistent with bound-constrained maximum likelihood (Byrd et al. 1995) and with the use of weakly informative constraints on dispersion or precision parameters when information is limited (Gelman 2006; Simpson et al. 2017). Second, we then refined the parameters by maximizing the beta log-likelihood under the usual positivity constraints. Full formulas, starting-value rules, and optimizer settings are discussed in Supplemental Appendix A. The statistical validations of the beta distribution

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assumptions for the Monte Carlo simulations are presented in Fig. B1 to B4 (Supplemental Appendix B). This includes the concentration parameters and Akaike Information Criterion differences, sample vs. fitted means comparisons, Probability Integral Transform diagnostics, and Kolmogorov–Smirnov tests (α = 0.05) (Akaike 1974; Burnham and Anderson 2002).

Revenue estimation from packout. All masses are in kilograms, and prices are in US dollars per kilogram (US$/kg). For each cell, the fitted beta distribution describes the likely range of packout for that orchard-year (which also captures weather or microclimate heterogeneity), cultivar, technology, and month. We converted packout to room-level net revenue using a standardized room mass at 2000 bins × cultivar-specific bin weight (Gallardo et al. 2025; Gallardo and Pedroso-Galinato 2023). The predicted cultivar-by-month prices from the three-stage-least squares (3SLS) price model, as well as the technology-by-month storage costs on a per-room basis, are described in the next section.

To convert packout uncertainty into revenue, we conducted a Monte Carlo simulation with 10,000 draws (with random seed fixed for reproducibility). In each draw and month, we sampled a packout from the fitted beta for each storage technology, translated it to a storage room-level revenue (room mass × predicted price × sampled packout minus storage costs), and recorded the results. We also compared the simulated monthly revenue outcomes by estimating the probability that DCA earns at least as much net revenue as CA (Glasserman 2004; Hardaker et al. 2015; Robert and Casella 1999). Exact computational details are in Supplemental Appendix B.

Component-based cost model. Monthly room costs are modeled as the sum of three components: (1) energy costs that scale with stored fruit mass (ton-months) and a technology-specific energy factor; (2) fixed operations and maintenance (O&M) plus capital costs reflecting infrastructure and baseline supervision for RA, CA, and DCA rooms; and (3) a DCA monitoring ("pod") add-on when applicable (Table 1). Our decomposition follows facility-level cost accounting in which cold storage costs are naturally partitioned into variable energy/electricity inputs and fixed costs dominated by depreciation (capital recovery) and permanent labor/overhead; survey evidence from conventional and controlled-atmosphere facilities indicates fixed costs comprise the majority share of total costs, with electricity/energy among the largest variable-cost items (Kart and Demircan 2015, 2014).

The RA baseline energy cost is $2 to $3 per ton-month (adjusted to current prices based on Mathia and Beals 1977). Refrigeration is the dominant end use in refrigerated-warehouse electricity use (~79% in typical benchmarking), so energy costs scale with stored ton-months (MidAmerican Energy 2019). Washington electricity prices are comparatively low (US Energy Information Administration 2025; Washington State Department of Commerce 2018), consistent with this baseline range. For the Washington baseline room (2000 bins; 1 bin = 925 lb), stored mass is ~925 short tons (Gallardo et al. 2025), implying an RA energy component of $1850 to $2775 per room-month before applying technology factors.

Energy factors capture incremental requirements beyond refrigeration for gas control and monitoring. CA storage operates gas-tight rooms at low oxygen (typically 1% to 3% O_2) with controlled CO_2 (typically 1% to 5% CO_2), commonly requiring nitrogen generation/air separation, CO_2 management (e.g., scrubbing), and continuous monitoring with automatic control (World Food Logistics Organization 2018); we represent this as 1.15 to 1.25 relative to RA (1.00) (Table 1). DCA adds more intensive sensing and supervisory control through repeated physiological measurements and dynamic setpoint adjustment (Fruit Growers News 2022; Storage Control Systems 2021) and is represented as 1.25 to 1.35 relative to RA. This representation is consistent with syntheses emphasizing the high gas-tightness and control requirements of DCA operation (Büchele et al. 2024). Because energy effects can be implementation-specific, DCA may reduce total heat loads (energy demand) relative to static CA in some contexts (e.g., by 8% to 16% in pear storage) (Phan et al. 2026). Table 1 reports ranges rather than point estimates. Life-cycle analyses of long fruit cold chains further underscore the relevance of the energy term in controlled-atmosphere decisions (du Plessis et al. 2024).

Fixed O&M + capital combines annualized capital recovery/lease amortization of cold-room infrastructure and atmosphere-control hardware with fixed O&M (maintenance, supervision, insurance/administrative overhead, and safety/compliance) (Table 1). CA and DCA rooms are assumed to be constructed to similarly high-tightness ("DCA-ready") standards based on industry expert communications and technical requirements for DCA operation (Büchele et al. 2024), so CA and DCA fixed-cost ranges are modeled as broadly comparable, with DCA differentiation captured primarily via monitoring/service add-ons. This fixed–variable separation is consistent with facility-level cost accounting, in which depreciation

Table 1. Component cost model: Monthly room costs by technology.

Technology	Energy factor[i]	Fixed O&M + capital ($/mo)[ii]	DCA monitoring ($/mo)[iii]	Total ($/mo)[iv]	Premium vs. CA ($)[v]
RA[vi]	1.00	7,704 to 9,387	0	9,554 to 12,162	−1,485 to −969
CA[vii]	1.15 to 1.25	8,395 to 10,178	0	10,523 to 13,647	Baseline
DCA[viii]	1.255 to 1.35	8,495 to 10,278	500 to 900	11,308 to 14,924	785 to 1,277

[i] Energy factors reflect technology-specific incremental energy requirements relative to RA (1.00). Ranges reflect uncertainty in incremental energy use under commercial operating conditions. CA targets low O_2 and manages CO_2 via gas handling and monitoring/control beyond refrigeration (World Food Logistics Organization 2018). DCA adds more intensive sensing and supervisory control via repeated measurements and dynamic setpoint adjustment (Fruit Growers News 2022; Storage Control Systems 2021).

[ii] Fixed O&M + capital combines (1) annualized capital recovery/lease amortization of the cold-room infrastructure and installed atmosphere-control hardware and (2) fixed operations and maintenance (routine maintenance, supervision, insurance/administrative overhead, safety/compliance). CA and DCA rooms are assumed to be constructed to similarly high-tightness ("DCA-ready") standards.

[iii] DCA monitoring is modeled as a separable operating add-on (sensors, data acquisition, software/interface, calibration/support; purchase vs. service models vary) rather than embedded in construction cost (Fruit Growers News 2022; Storage Control Systems 2021). The $500 to $900/mo. range is treated as a sensitivity bracket informed by industry expert communications.

[iv] Monthly total room cost equals energy cost + fixed O&M + capital + DCA monitoring (if applicable). Energy cost is computed as (baseline RA energy cost of $2 top $3 per ton-mo.) × (stored mass in ton-mo.) × (energy factor). For the Washington baseline room (2000 bins; 925 lb/bin ~ 925 short tons), this yields an RA energy component of $1850 to $2775 per room-mo. (Gallardo et al. 2025), with baseline energy levels supported by refrigerated-warehouse benchmarking and Washington electricity prices (MidAmerican Energy 2019; US Energy Information Administration 2025).

[v] Premium vs. CA is calculated as total (technology) − total (CA) using paired comparisons (low–low and high–high); the reported interval uses the minimum and maximum of those two paired values. Negative values indicate cost savings relative to CA; positive values indicate a cost premium.

[vi] Regular atmosphere refers to storage under standard atmospheric composition (no active control of O_2 and CO_2 beyond normal ventilation and refrigeration).

[vii] CA slows ripening by maintaining low oxygen and managing carbon dioxide using gas-handling equipment and continuous monitoring/control (Thompson et al. 2018; World Food Logistics Organization 2018).

[viii] Dynamic CA approach that uses physiological monitoring and dynamic adjustment of low-oxygen management during storage to reduce the risk of low-O_2 injury/fermentation while maintaining quality (Fruit Growers News 2022; Storage Control Systems 2021; Thewes et al. 2024).

CA = controlled atmosphere; DCA = dynamic controlled atmosphere; O&M = operations and maintenance; RA = regular atmosphere.

and energy are major cost categories (Kart and Demircan 2015, 2014).

For DCA rooms, monitoring is modeled as a separable add-on of $500 to $900 per room-month (Table 1), representing sensors, data acquisition, software/interface, calibration/support, and licensing/service models. This treatment is consistent with commercial DCA platforms that use an in-room test enclosure ("pod") and controller to guide dynamic setpoints while limiting risk to the full room (Fruit Growers News 2022; Storage Control Systems 2021). Costs are reported monthly for accounting consistency; for interpretation, monthly totals can be converted to $/bin-season by multiplying by storage season length and dividing by 2000 bins.

Monthly price forecasting and seasonal price dynamics. This subsection details the data sources for the econometric model analyzing monthly apple price fluctuations between harvest seasons to identify optimal marketing times, driven by seasonal supply changes affecting storage outcomes and profitability. We use weekly free on board (FOB) price data, which are the prices negotiated by the packing house on behalf of the grower and excludes transportation costs and weekly shipment volumes for organic 'Gala' and 'Honeycrisp' apples from the Washington Tree Fruit Association. The units of these prices are in dollars per 40-lb box (18.14 kg) as the unit of the shipment volumes is a 40-lb box (18.14 kg). This allows us to capture detailed market dynamics effectively. Weekly data have been combined into monthly observations from 2017–24, shown in Table 2. Macroeconomic indicators are also used in the analysis, including monthly wages (US Bureau of Labor Statistics 2025a), the federal funds rate (US Federal Reserve System 2025), and the fresh fruits producer price index (PPI) (US Bureau of Labor Statistics 2025b).

Price model. We estimate monthly organic FOB prices (US$/kg) with a simultaneous system for price and shipments, fit separately for 'Gala' and 'Honeycrisp'. The system is estimated by 3SLS (Zellner and Theil 1962), which treats simultaneity and endogeneity using instrumental variables and gains efficiency by exploiting cross-equation error correlation (Greene 2003; Wooldridge 2010; Zellner and Theil 1962).

Let m index months, September is the omitted category for seasonality. We define $P^O_{c,m}$ as the organic FOB price for cultivar c; $P^C_{c,m}$ is the conventional FOB price; $Q^O_{c,m}$ is the average organic shipments (kg); W_m represents the monthly wages; FFR_{m-1} represents federal funds rate (lagged 1 month); $\mathrm{PPI}^{\mathrm{FF}}_{m-1}$ is the producer price index for fresh fruits (lagged 1 month); and $D_{s,m}$ is the monthly indicator variable for $s \in \{October, \ldots, August\}$, where September is omitted.

For 2 month-lagged specification (baseline), the price is shown in Eq. [1], and the shipments are shown in Eq. [2]. For 1 month-lagged alternative (parsimony check), the price is shown in Eq. [3], and the shipments are shown in Eq. [4].

$$P^O_{c,m} = \beta_0 + \beta_1 P^O_{c,m-1} + \beta_2 P^O_{c,m-2} + \beta_3 P^C_{c,m} + \beta_4 P^C_{c,m-1} + \beta_5 P^C_{c,m-2} + \beta_6 \mathrm{FFR}_{m-1} + \beta_7 \mathrm{PPI}^{\mathrm{FF}}_{m-1} + \beta_8 Q^O_{c,m} + \sum_{s\neq \mathrm{Sep}} \varphi_s D_{s,m} + u_{1m} \quad [1]$$

$$Q^O_{c,m} = \alpha_0 + \alpha_1 Q^O_{c,m-1} + \alpha_2 Q^O_{c,m-2} + \alpha_3 P^C_{c,m} + \alpha_4 P^C_{c,m-1} + \alpha_5 P^C_{c,m-2} + \alpha_6 W_m + \sum_{s\neq \mathrm{Sep}} \delta_s D_{s,m} + u_{2m} \quad [2]$$

$$P^O_{c,m} = \beta_0 + \beta_1 P^O_{c,m-1} + \beta_2 P^C_{c,m} + \beta_3 P^C_{c,m-1} + \beta_4 \mathrm{FFR}_{m-1} + \beta_5 \mathrm{PPI}^{\mathrm{FF}}_{m-1} + \beta_6 Q^O_{c,m} + \sum_{s\neq \mathrm{Sep}} \varphi_s D_{s,m} + u_{1m} \quad [3]$$

$$Q^O_{c,m} = \alpha_0 + \alpha_1 Q^O_{c,m-1} + \alpha_2 P^C_{c,m} + \alpha_3 P^C_{c,m-1} + \alpha_4 W_m + \sum_{s\neq \mathrm{Sep}} \delta_s D_{s,m} + u_{2m} \quad [4]$$

The predicted organic price entering Eq. [A8] of the revenue section, discussed in Supplemental Appendix A2, is as follows:

$$\hat{P}_{cm} \equiv \hat{P}^O_{c,m} \quad [5]$$

We treat $Q^O_{c,m}$ as endogenous in the price equation. The instrument set is the union of exogenous variables across the system. In particular, W_m is excluded from the price equation (affecting shipments or supply only), while FFR_{m-1} and $\mathrm{PPI}^{\mathrm{FF}}_{m-1}$ are excluded from the shipment equation (shifting price but not contemporaneous shipments). 3SLS then uses these instruments and the estimated cross-equation disturbance covariate to deliver consistent and asymptotically efficient estimates under standard assumptions (Greene 2003; Wooldridge 2010; Zellner and Theil 1962). Taken from the two-lag specification using instrumented $Q^O_{c,m}$ and observed covariates, monthly effects are interpreted relative to September.

Parameter estimates and Monte Carlo simulations are calculated using an online, high-level programming language for data analysis (Python, ver. 3.10.12; Python Software Foundation 2025) and statistical software (Stata, ver. 18.5; StataCorp 2024). We present several checks in Supplemental Appendix C asserting the robustness of the price modeling [such as the Durbin–Wu–Hausmann Test (Table C1), the Hausman test (Table C2), White's heteroscedascity test (Table C3), the overidentification test (Table C4), and the lag length criteria test (Table C5)].

Results and Discussion

DCA is the more economical option under specific timing, site, and weather contexts. For 'Gala', the probability that DCA exceeded CA surpassed 50% from March and remained elevated into summer. For 'Honeycrisp', dominance was orchard- and year-specific with no sustained summer rise. Adverse harvest weather (heat-stress conditions) reduced dominance in both cultivars. The 'Gala' pattern is consistent with cultivar–environment effects on size/color and firmness loss (Argenta et al. 2022), and the 'Honeycrisp' sensitivity aligns with phenology-window weather links to soft-scald risk (Lachapelle et al. 2013; Moran et al. 2009).

Storage technology and duration effects on apple quality

For both organic 'Gala' and 'Honeycrisp' apples, storage technology varies significantly by cultivar, orchard location, and storage duration. As shown in Table 3, DCA demonstrates superior performance for 'Gala' apples across all storage durations, achieving 91.7% (IQR, 88.6% to 97.3%) marketable fruit at 9 months compared with 79.4% for CA (IQR, 73.0% to 83.7%) and 71.0% for RA (IQR, 59.1% to 77.5%). For 'Honeycrisp' apples, orchard-specific patterns emerge. While CA outperforms DCA at 'Honeycrisp' orchard 1 (Othello) with 98.4% vs. 85.6% at 9 months, DCA shows competitive performance at 'Honeycrisp' orchard 2 (Quincy) with 87.1% compared with CA's 89.1%. Notably, DCA consistently outperforms RA storage across all cultivar–orchard-year combinations, demonstrating substantial advantages over conventional storage methods.

Table 2. Summary statistics for price and shipment volumes of organic 'Gala' and 'Honeycrisp' and other variables.

Variables	Count	Mean	*SD*	Minimum	Maximum
'Gala'					
Organic FOB (US$/box[i])	125.00	37.50	7.78	26.87	68.09
Organic average shipments (thousand box)	101.00	86.92	26.16	7.50	149.20
Conventional FOB price (US$/box)	125.00	23.48	3.66	17.72	35.73
Conventional average shipments (thousand box)	101.00	400.21	112.80	160.63	621.75
'Honeycrisp'					
Organic FOB price[ii] (US$/box)	117.00	69.96	14.36	45.89	106.47
Organic average shipments (thousand box)	97.00	44.59	20.23	2.00	85.47
Conventional FOB price (US$/box)	117.00	49.72	11.44	27.11	86.58
Conventional average shipments (thousand box)	98.00	208.07	60.22	12.00	360.45
Other variables					
Federal funds rate	125.00	1.72	1.86	0.05	5.33
Producer price index of fresh fruits	125.00	148.47	19.54	110.80	212.76

[i] A box weighs 40 lb or 18.14 kg.

[ii] FOB prices are negotiated by the packing house on behalf of the grower and excludes transportation costs and weekly shipment volumes.

FOB = free on board; *SD* = standard deviation.

Table 3. Marketable fruit percentage ranges (minimum to maximum from 10,000 Monte Carlo simulations, without disorders and decay) by storage technology and orchard location for organic 'Gala' and 'Honeycrisp' apples.

		Regular atmosphere (%)		Controlled atmosphere (%)		Dynamic controlled atmosphere (%)	
Apple cultivar	Storage duration	Mean	IQR	Mean	IQR	Mean	IQR
'Gala' orchard 1	3 mo. + 7 d	99.8	99.7 to 100	99.7	99.6 to 100	100.0	100.0 to 100
	6 mo. + 7 d	96.2	94.6 to 99.2	93.8	91.2 to 98.4	98.4	97.6 to 100
	9 mo. + 7 d	71	59.1 to 77.5	79.4	73.0 to 83.7	91.7	88.6 to 97.3
'Honeycrisp' orchard 1	3 mo. + 7 d	98.9	98.4 to 99.9	95	92.5 to 98.6	85.7	78.6 to 99.1
	6 mo. + 7 d	91.5	87.4 to 95.8	97.7	96.5 to 99.9	91.7	87.6 to 99.5
	9 mo. + 7 d	80.7	71.3 to 95.8	98.4	97.6 to 99.4	85.6	78.9 to 99.0
'Honeycrisp' orchard 2	3 mo. + 7 d	81.8	75.0 to 86.2	86.7	81.3 to 90.2	79.6	74.2 to 85.0
	6 mo. + 7 d	77.1	69.2 to 83.9	87.8	83.2 to 93.0	66.2	54.2 to 81.9
	9 mo. + 7 d	65.5	50.2 to 86.9	89.1	88.8 to 89.4	87.1	83.8 to 92.0

Interquartile range (IQR) represents the range between the 25th and 75th percentiles of marketable fruit percentages from Monte Carlo simulations. The range contains 50% of simulation outcomes (25th to 75th percentiles), indicating variability around the mean of marketable fruit percentage.

The observed storage patterns for organic 'Honeycrisp' apples differed notably from organic 'Gala' apples, potentially due to environmental factors such as heat waves during the evaluated harvest seasons (Kawhena et al. 2021). 'Honeycrisp' shows greater variability across orchards, with 'Honeycrisp' orchard 2 generally exhibiting lower DCA performance than 'Honeycrisp' orchard 1, suggesting that orchard-specific factors influence storage technology effectiveness.

Price dynamics and market conditions

Price determinants and seasonal dynamics. Table 4 shows the 3SLS model regression results for organic 'Gala' and 'Honeycrisp' apple prices, analyzing monthly pricing dynamics over the harvest year with September as the baseline. For organic 'Gala' apple prices, autoregressive price terms significantly shape current prices. The 1 month lag of organic apple prices ($P^{O}_{c,m-1}$) has a notable influence (0.42), while the 2 month lag ($P^{O}_{c,m-2}$) also contributes positively, although to a lesser extent (0.16). Seasonally, price premiums become significant starting in November (3.89), peak in March (6.61), and remain elevated through July (2.98), compared with September of the previous year. This indicates sustained market demand or limited availability, making winter and spring optimal periods for selling organic 'Gala' apples. The federal funds rate (FFR_{m-1}) negatively affects prices (−0.48), although changes in competing fruit prices (PPI^{FF}_{m-1}) are not significant. Higher average shipment volumes exert downward pressure on organic 'Gala' prices (−0.11), emphasizing the importance of managing supply volumes.

Organic 'Honeycrisp' apple prices exhibit stronger autoregressive behavior, with a substantial influence from the 1 month delay (0.71), indicating price rigidity and persistent market momentum. The 2 month lag negatively affects prices, although only marginally significantly (−0.22). Prices show significant seasonal premiums beginning in November (5.69), dramatically peaking in July (11.10), compared with September of the previous year. There are strong seasonal demand and potential shortages in late spring and summer. The FFR_{m-1} lowers organic 'Honeycrisp' prices (−0.73), increasing borrowing and holding costs. The PPI^{FF}_{m-1} (0.13) indicates competition and substitution effects, urging organic 'Honeycrisp' growers to monitor rival market prices. Similar to organic 'Gala', higher shipment volumes decrease organic 'Honeycrisp' prices (−0.14), highlighting the importance of managing supply volumes.

When comparing the two, organic 'Honeycrisp' apples have higher price persistence and seasonal premiums than organic 'Gala', especially in summer, likely due to consumer preferences or less volume availability. Organic 'Honeycrisp' prices are also more affected by external factors like competing fruit prices (PPI^{FF}_{m-1}), urging growers to monitor related markets. Both cultivars are negatively affected by rising interest rates and shipment volumes, indicating common supply-side pressures.

Price predictions. Table 5 presents the predicted organic apple prices per 40-lb box (18.14 kg) and per pound calculated using the 3SLS model coefficient estimates for organic 'Gala' and 'Honeycrisp' cultivars. The prices per pound were derived by dividing the predicted prices per box by 40, in accordance with the standard weight of an apple box (US Department of Agriculture 1992). Monthly dynamics are analyzed to highlight price movements relative to September, the starting point of the harvest season.

Organic 'Gala' apples exhibit considerable seasonal variation in the predicted prices per pound. Prices are lowest in September at $0.40/lb ($0.88/kg), the start of harvest. Prices increase steadily, reaching a peak in March at $0.56/lb ($1.23/kg), which is 6 months after harvest begins. The peak results from a limited supply combined with ongoing consumer demand throughout winter and the start of spring. As the new harvest approaches, prices slowly begin to drop. Given these anticipated prices, organic 'Gala' apple growers might strategically manage their storage and sales from January when prices are at $0.54/lb ($1.19/kg) to May at $0.55/lb ($1.21/kg) to maximize their seasonal profits.

Table 4. Parameter estimates for the model including two lags and monthly indicators.

Variable	Organic 'Gala' prices	Organic 'Honeycrisp' prices
Intercept	14.21 (3.40)***	5.27 (7.60)
$P^{O}_{c,m-1}$ (FOB Organic$_{t-1}$)	0.42 (0.12)***	0.71 (0.13)***
$P^{O}_{c,m-2}$ (FOB Organic$_{t-2}$)	0.16 (0.07)**	−0.22 (0.11)*
$P^{C}_{c,m}$ (FOB Conventional)	0.02 (0.13)	0.17 (0.18)
$P^{C}_{c,m-1}$ (FOB Conventional$_{t-1}$)	0.09 (0.21)	0.05 (0.17)
$P^{C}_{c,m-2}$ (FOB Conventional$_{t-2}$)	0.1 (0.13)	0.003 (0.10)
FFR_{m-1}	−0.48 (0.10)***	−0.73 (0.36)*
PPI^{FF}_{m-1}	0.01 (0.01)	0.13 (0.04)***
September	Baseline	Baseline
October	1.08 (1.18)	1.09 (2.25)
November	3.89 (1.15)***	5.69 (1.95)***
December	4.52 (1.19)***	3.56 (2.32)
January	5.73 (1.10)***	4.41 (2.56)*
February	5.99 (1.12)***	5.27 (2.52)**
March	6.61 (1.09)***	7.73 (2.99)**
April	5.67 (1.08)***	5.91 (2.97)*
May	5.83 (1.10)***	8.63 (2.76)***
June	4.90 (1.18)***	8.86 (4.12)**
July	2.98 (1.34)**	11.10 (3.16)***
August	0.58 (1.44)	6.28 (3.36)*
$Q^{O}_{c,m}$ (average shipment organic)	−0.11 (0.02)**	−0.14 (0.06)**
Observations	125.00	117.00
R^2	0.796	0.822
Estimator	GLS	GLS
Covariance estimator	Robust	Robust
No. of equations	2	2

* = $P < 0.1$, ** = $P < 0.05$, *** = $P < 0.01$.

The standard errors are in parentheses. FOB = free on board.

Table 5. Predicted packing house door prices for organic 'Gala' and 'Honeycrisp' apples.

	Price ($)			
	Organic 'Gala'		Organic 'Honeycrisp'	
Month	Per box[i]	Per pound[ii]	Per box	Per pound
September	15.98	0.40	57.43	1.44
October	17.06	0.43	58.52	1.46
November	19.88	0.50	63.12	1.58
December	20.50	0.51	60.99	1.52
January	21.71	0.54	61.84	1.55
February	21.97	0.55	62.70	1.57
March	22.59	0.56	65.15	1.63
April	21.65	0.54	63.34	1.58
May	21.81	0.55	66.05	1.65
June	20.88	0.52	66.29	1.66
July	18.96	0.47	68.53	1.71
August	16.56	0.41	63.70	1.59

[i] A box weighs 40 lb or 18.14 kg.
[ii] 1 pound = 0.4357 kg.

Predicted prices per pound for organic 'Honeycrisp' apples demonstrate pronounced seasonal fluctuations. Prices are lowest at harvest in September at $1.44/lb ($3.17/kg) and increase progressively, peaking in July at $1.71/lb ($0.377/kg), 10 months postharvest. This extended price increase indicates either sustained demand coupled with tightening supply or significant storage costs associated with higher probability of losses due to prolonged storage periods. Prices remain elevated into August at $1.59/lb ($3.51/kg), significantly higher than the harvest month. Organic 'Honeycrisp' growers face critical decisions regarding storage investments and may greatly benefit from delayed market entry until late spring or early summer despite higher storage costs.

Revenue and profitability implications

Revenue outcomes given different storage technologies and uncertainty bands. Table 6 displays the distribution of net revenue differences (DCA − CA) derived from the Monte Carlo simulation of marketable percentages and the predicted monthly prices described above, highlighting only the cases of peak seasonal prices. Table 6 reports both median outcomes and 10th and 90th percentiles. For organic 'Gala' apples, the highest recorded in May, which corresponds to the price peak, shows a 68% probability of positive difference, with median revenue difference of $4816 in May 2024. Revenues could be as low as −$116,729 at the 10th percentile (May 2022) to $448,217 at the 90th percentile (May 2024). For organic 'Honeycrisp', July represents the price peak period. The highest probability of positive difference is 79% and the median revenue difference of $197,380 recorded in 'Honeycrisp' orchard 2 on Jul 2023. Revenues could dip as low as −$2,085,182 (Jul 2022, 'Honeycrisp' orchard 1) in the worst-case scenario at the 10th percentile to a high of $415,643 (Jul 2023, 'Honeycrisp' orchard 2) in the best scenario at the 90th percentile. These wide uncertainty bands reflect the compounding packout variability with price seasonality and cost uncertainty, emphasizing the importance of probabilistic rather than deterministic analysis.

Monte Carlo simulation results: Probability of DCA dominance. Figure 1A–1C presents the probability that DCA generates higher net revenues than CA across storage technologies and seasons, revealing distinct seasonal patterns by cultivar, orchard location, and year. For organic 'Gala' apples, DCA dominance probability follows a consistent seasonal progression but exhibits substantial yearly variation. Spring performance shows increasing strength over time, rising from 37.6% in 2022 to 57.0% in 2023 and 67.7% in 2024. Summer patterns demonstrate the most pronounced yearly variation, with 2024 achieving exceptional performance (91.8%) compared with 2022 (52.0%) and 2023 (50.4%). This clear seasonal progression reflects DCA's superior ability to maintain fruit quality as storage extends, with the probability exceeding 50% beginning in spring for 2024, suggesting that DCA becomes economically favorable for storage periods exceeding 6 months.

For organic 'Honeycrisp' apples, orchard-specific patterns reveal significant location-based differences compounded by extreme yearly variability. 'Honeycrisp' orchard 1 (Othello, Adams County) demonstrates the most volatile patterns, with 2024 showing exceptional spring performance (100.0%), while 2022 exhibited minimal benefits (6.4% spring, 2.8% summer) and 2023 showed moderate performance (34.0% spring, 16.7% summer). Summer patterns at this location show increasing performance over time, with probabilities of 2.8% (2022), 16.7% (2023), and 42.0% (2024). In contrast, 'Honeycrisp' orchard 2 (Quincy, Grant County) shows opposing patterns, with 2022 achieving stronger summer performance (77.0%) and moderate spring benefits (47.7%), and 2023 showing strong summer results (78.6%) with moderate spring performance (34.9%). Meanwhile, 2024 demonstrated poor performance across all seasons (0.1% spring, 3.2% summer). This location-specific variability explains why aggregate results may mask the underlying complexity (see Supplemental Appendix F), with some orchard × year combinations that strongly favor DCA in specific seasons, while others consistently support CA adoption. For completeness, we also present CA dominance over RA in Supplemental Appendix D (Fig. D1).

Variability in profitability outcomes

Orchard effects where DCA shows economic advantage. Performance varied strongly by orchard as described in Table 7, particularly for 'Honeycrisp'. 'Honeycrisp' orchard 1 reached 100% DCA success probability in Spring 2024 with median revenue advantages of $179,751 (range, $99,797 to $292,004). 'Honeycrisp' orchard 2 achieved 77.0% success in Summer 2022 and 78.6% success in Summer 2023 with median advantages of $237,450 (Summer 2022 range, −$500,278 to $365,300) to $187,663 (Summer 2023 range, −$239,936 to $415,643) but performed poorly in 2024. For 'Gala', orchard 1 showed strong summer advantages in 2024, with 91.8% success probability and a median DCA-CA revenue advantage of $170,488 (range, $2447 to $603,075).

Table 6. Distribution of net revenue differences (DCA − CA) from Monte Carlo simulation, showing median outcomes and uncertainty ranges by cultivar, orchard location, and peak period.

Cultivar/orchard	Peak period[i]	Median revenue difference ($)	Revenue difference ($) P10[ii]	Revenue difference ($) P90[ii]	Probability positive difference (%)[iv]
'Gala' orchard 1	May 2022	−1,301	−116,729	45,578	38
	May 2023	573	−2,254	32,023	57
	May 2024	4,816	−2,043	448,217	68
'Honeycrisp' orchard 1	Jul 2022	−1,128,377	−2,085,182	−290,075	3
	Jul 2023	−2,153	−80,460	563	16
	Jul 2024	−942	−74,453	78,430	42
'Honeycrisp' orchard 2	Jul 2022	243,112	−500,278	365,300	77
	Jul 2023	197,380	−219,510	415,643	79
	Jul 2024	−327,593	−606,671	−91,331	3

[i] Peak periods represent months with the highest predicted market prices: May for 'Gala' and July for 'Honeycrisp'.
[ii] P10 percentiles show the 10th (lowest 10%) percentile from 10,000 Monte Carlo simulations, representing the uncertainty range.
[iii] P90 percentiles show the 90th (highest 10%) percentile from 10,000 Monte Carlo simulations, representing the uncertainty range.
[iv] Positive probability indicates the percentage of scenarios where DCA generates higher net revenue compared with CA.
DCA = controlled atmosphere dynamic; CA = controlled atmosphere.

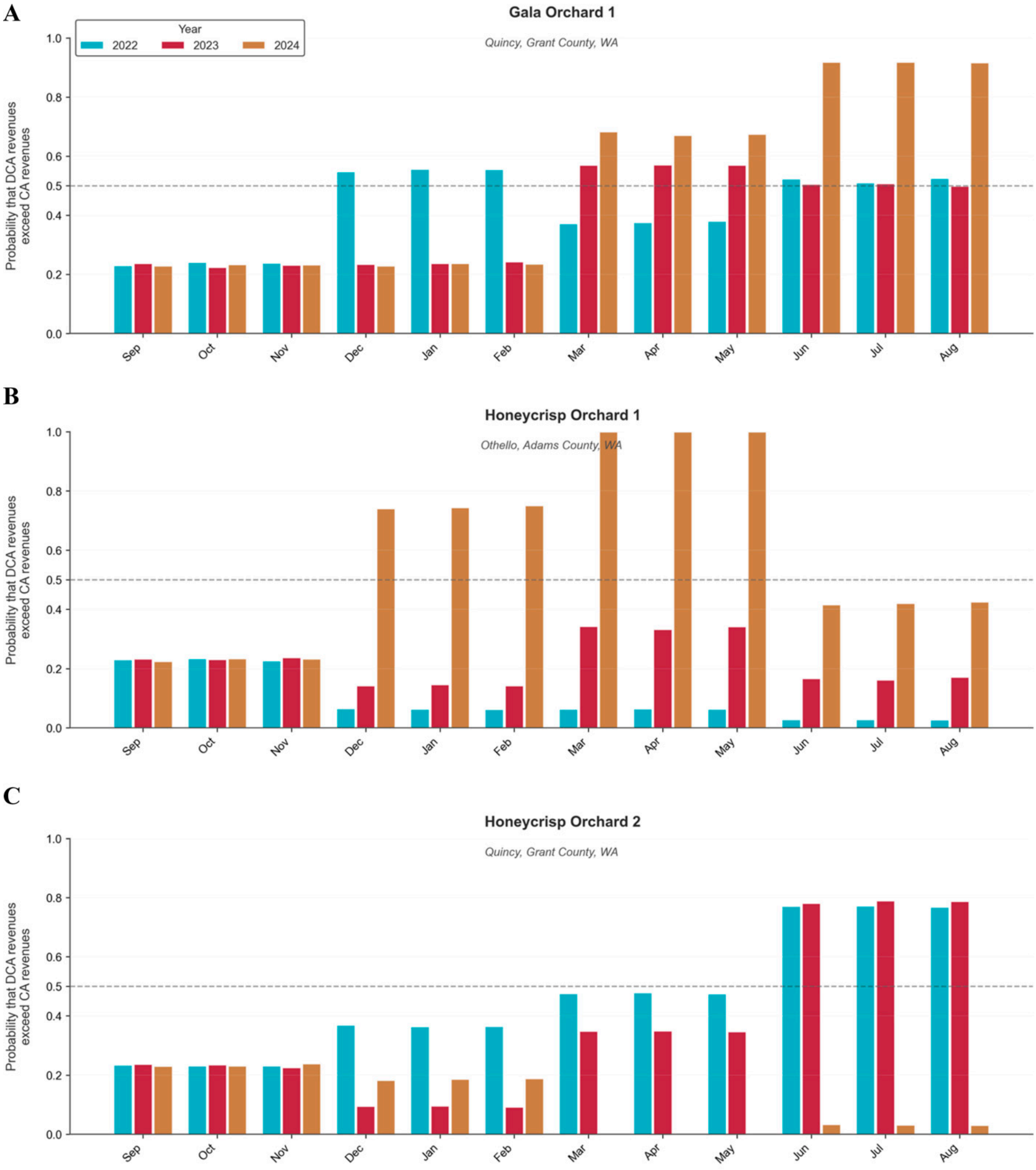

Fig. 1. Probability that dynamic controlled atmosphere (DCA) revenues exceed controlled atmosphere (CA) revenues by month, cultivar, and orchard-year. (**A**) 'Gala' orchard 1 (Quincy, Grant County, WA). (**B**) 'Honeycrisp' orchard 1 (Othello, Adams County, WA). (**C**) 'Honeycrisp' orchard 2 (Quincy, Grant County, WA). The bars represent monthly probabilities for the years 2022, 2023, and 2024.

Weather sensitivity and risk management. Figure 2A–2C compares DCA dominance probabilities under normal vs. adverse weather conditions (harvest heat stress). Under normal conditions, 'Gala' shows moderate DCA performance in Fig. 2A with average dominance probabilities of 56.0% (January to August). However, under heat stress, dominance probability decreases to 47.5% (an 8.5-percentage point reduction), indicating that heat stress reduces DCA dominance for 'Gala' apples, consistent with physiological expectations. For 'Honeycrisp', orchard-specific patterns reveal significant location-based differences in weather sensitivity. 'Honeycrisp' orchard 1 in Fig. 2B exhibits strong negative weather sensitivity, with dominance probabilities falling from 72.0% under normal conditions to only 13.9% under heat stress (a 58.1-percentage point decline). In contrast, 'Honeycrisp' orchard 2 in Fig. 2C shows moderate negative

Table 7. Orchard-specific DCA economic advantages and success probabilities by season and year.

Orchard	Year	Season[i]	DCA success probability (%)[ii]	DCA revenue advantage ($)[iii]
'Gala' orchard 1	2022	Spring	37.6	−1,335
	2022	Summer	52.0	774
	2023	Spring	57.0	572
	2023	Summer	50.4	77
	2024	Spring	67.7	4,816
	2024	Summer	91.8	170,488
'Honeycrisp' orchard 1	2022	Spring	6.4	−76,620
	2022	Summer	2.8	−1,095,422
	2023	Spring	34.0	−1,411
	2023	Summer	16.7	−2,153
	2024	Spring	100.0	179,751
	2024	Summer	42.0	−942
'Honeycrisp' orchard 2	2022	Spring	47.7	−1,783
	2022	Summer	77.0	237,450
	2023	Spring	34.9	−42,172
	2023	Summer	78.6	187,663
	2024	Spring	0.1	−1,224,912
	2024	Summer	3.2	−315,028

[i] Storage seasons when DCA shows meaningful economic advantages. Spring (March to May) represents the transition period when DCA advantages begin to emerge as storage extends beyond 6 months. Summer (June to August) represents the peak period for DCA economic advantage, when extended storage (7 to 9 months) maximizes the technology's quality preservation benefits and coincides with higher seasonal prices.

[ii] Percentage chance that DCA outperforms CA storage in revenue generation.

[iii] Median additional net revenue per room when using DCA instead of CA storage.

CA = controlled atmosphere; DCA = dynamic controlled atmosphere.

weather sensitivity, with dominance probabilities decreasing from 44.9% under normal conditions to 30.9% under heat stress, representing a 14-percentage point reduction. This orchard-level heterogeneity demonstrates that weather sensitivity varies substantially by location, likely reflecting differences in microclimates, preharvest horticultural management, and harvest timing that influence how heat stress affects DCA storage performance.

Our analysis of adverse weather conditions, on average, especially heat stress proximate to harvest, shows reduced DCA dominance probabilities for 'Honeycrisp' cultivars (Torres and Mattheis 2024). In 2022, a region-wide early-September heat wave with unusually warm nights and elevated humidity coincided with the harvest window and corresponded with weaker DCA performance, particularly for 'Honeycrisp' (NOAA National Centers for Environmental Information 2022; Pratt 2022). The stratified analysis reveals that orchard location interacts with weather events to influence storage outcomes, albeit the study only captured the general regional climate. The Grant County orchards ('Gala' orchard 1 and 'Honeycrisp' orchard 2, both located in Quincy, WA) and 'Honeycrisp' orchard 1 in Othello, WA (Adams County), are characterized as cold semiarid settings with hot dry summers (Plant Maps 2024a, 2024b; Washington State University AgWeatherNet 2025a, 2025b).

Importantly, environmental conditions during the growing season help explain cultivar-specific storage behavior observed over the review period. For 'Gala', cooler sites tend to produce larger, redder fruit with higher start index at harvest but faster softening during storage. Warmer sites show more *Glomerella cingulata* spot, whereas colder sites are associated with greater risks of watercore, CO_2 injury, and diffuse flesh browning (observed for late cultivars and mechanistically relevant to low-O_2 sensitivity) (Argenta et al. 2022). For 'Honeycrisp', susceptibility to soft scald rises when the season combines cool and wet conditions shortly after bloom (0 to 30 d from full bloom), heavy rain in mid-development (31 to 60 d), and warm spells as fruit reach ∼50 to 80% final size; low internal ethylene at harvest also tracks higher soft-scald risks (Lachapelle et al. 2013). These phenology-linked weather drivers align with 2022's pattern of a cool spring followed by an intense early-September heat event, which plausibly elevated 'Honeycrisp' disorder risk at both locations and amplified the DCA performance penalty that year (NASA Earth Observatory 2022; NOAA, National Centers for Environmental Information 2022). These results are robust to the presence of outliers as described in Supplemental Appendix E.

Although Quincy (Grant) and Othello (Adams) are adjacent and experience similar synoptic events, weather analyses reveal meaningful climate differences between the two orchard sites that help explain the observed storage outcome heterogeneity. the principal signals were shared across sites. In 2022, Othello was 2.2 to 2.7 degrees warmer than Quincy during critical periods (harvest and preharvest), received less precipitation (21.2 vs. 25.7 inches), and had lower relative humidity during harvest (50.9% to 59.6% vs. 54.1% to 60.4%). The warmer and drier conditions in Othello during critical fruit development and harvest periods may have amplified heat stress effects on fruit quality, explaining greater weather sensitivity at that location (Washington State University AgWeatherNet 2025a, 2025b). This weather sensitivity implies that climate variability can shift the relative economics of storage technologies in site-specific ways, with greater volatility favoring more robust methods.

Broader implications for storage technology adoption

The comprehensive analysis of DCA storage economics reveals a broader industry implication that extends beyond adoption decisions. The study results demonstrate that DCA technology adoption will likely follow a specific pattern associated with preharvest horticultural management, weather-related conditions, and cultivar, rather than uniform industry-wide implementation. The dramatic variation in performance across cultivars, orchards, seasons, and years, which ranges from 0% to 100% success probabilities, indicates that successful DCA adoption requires multidimensional decision-making frameworks.

The study's weather sensitivity analysis adds an important layer in the adoption strategy, revealing that environmental conditions and local microclimates can either enhance or diminish DCA effectiveness depending on orchard locations. This apparent environmental dependency, combined with the observed cultivar-specific patterns, creates opportunities for dynamic market segmentation in which storage strategies can be optimized based on multiple factors such as seasonal conditions, weather patterns, and multiyear performance trends.

These comprehensive findings point to specific research and development priorities, including multiyear performance prediction models, weather-responsive DCA protocols, and cultivar-specific storage optimization strategies that account for both spatial and temporal variability. The study also suggests that extension services and agricultural policy should move beyond static recommendations toward adaptive, location-specific guidance that integrates cultivar characteristics, environmental conditions, seasonal patterns, and temporal performance trends into decision-making frameworks.

Summary and Conclusion

This study evaluated the economic impact of adopting DCA storage technology on preservation quality, pricing dynamics, and overall profitability of organic 'Gala' and 'Honeycrisp' apples under uncertainty using Monte Carlo simulation with beta-distributed packout rates. Our findings reveal that storage technology significantly affects fruit quality and grower revenue outcomes, although the magnitude of these impacts varies notably by cultivar and is strongly influenced by orchard location and weather conditions.

Using Monte Carlo simulation with 10,000 iterations per scenario, we found that DCA showed strong seasonal progression for organic 'Gala' apples, with dominance probability increasing from 37.6% in Spring 2022 to 91.8% in Summer 2024. The median revenues from organic 'Gala' apples stored under

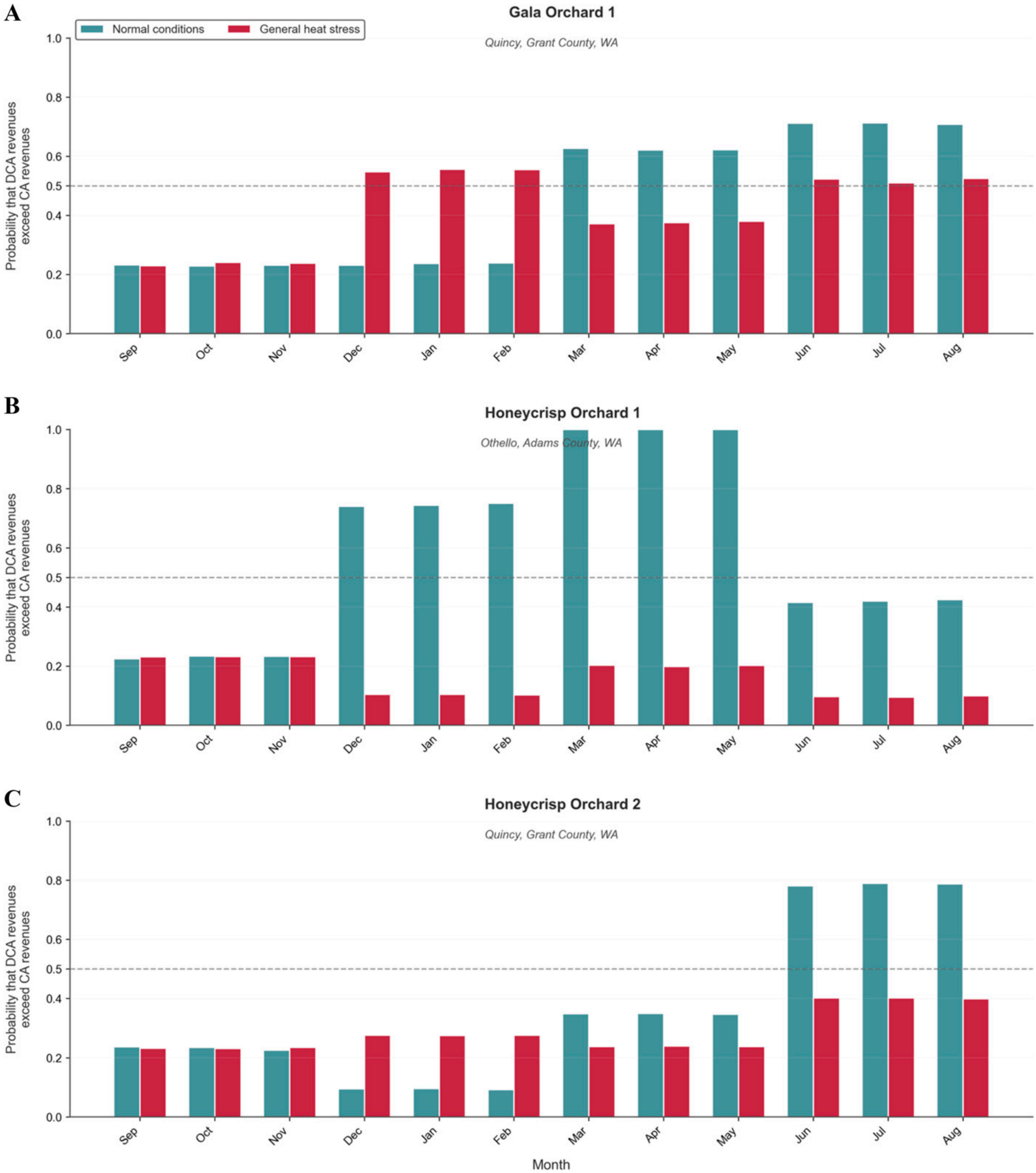

Fig. 2. Weather sensitivity - Probability that dynamic controlled atmosphere (DCA) revenues exceed controlled atmosphere (CA) revenues under normal vs. general heat stress conditions by month, cultivar, and orchard. (**A**) 'Gala' orchard 1 (Quincy, Grant County, WA). (**B**) 'Honeycrisp' orchard 1 (Othello, Adams County, WA). (**C**) 'Honeycrisp' orchard 2 (Quincy, Grant County, WA).

DCA exceed CA revenues by $170,488 per room during peak periods (Summer 2024), although with considerable uncertainty. This advantage must be weighed against the additional monthly cost of DCA ($785 to $1277 per room relative to CA), yielding positive expected net returns for storage periods exceeding 6 months.

In contrast, organic 'Honeycrisp' exhibited significant orchard-level heterogeneity in storage outcomes. 'Honeycrisp' orchard 1 achieved exceptional performance with 100% DCA success probability in Spring 2024 and median revenue advantages of $179,751, while 'Honeycrisp' orchard 2 showed variable performance with 77.0% to 78.6% success in summer months (2022–23). Overall, 'Honeycrisp' showed substantial location-based differences in economic outcomes, with mean DCA dominance probability of 30.9% across all scenarios. Weather sensitivity analysis revealed critical orchard-specific patterns that significantly affected DCA adoption decisions. For 'Honeycrisp' orchard 1, general heat stress reduced the probability of DCA dominance from 72.0% to 13.9% (a 58.1-percentage point decline), whereas 'Honeycrisp' orchard 2 showed a more moderate reduction, with probabilities decreasing from 44.9% to 30.9% (a 14.0-percentage point decline) under general heat stress conditions. These two orchards exhibited different microclimates, which explains the divergent weather sensitivity patterns. 'Gala' apples demonstrated moderate weather sensitivity, with dominance probability declining from 56.0% to 47.5% (an 8.5-percentage point reduction) under general heat stress conditions, consistent with physiological expectations that heat stress reduces fruit quality. Additional 'Gala' orchards are needed to enable time series comparisons across different microenvironments.

Meanwhile, the price model identified key market factors, showing autoregressive behavior in apple prices and strong seasonal demand. Higher shipment volumes and federal fund rates negatively affected organic 'Gala' and 'Honeycrisp' prices, highlighting the need for controlled market releases to optimize pricing. The 3SLS approach addressed simultaneity between prices and shipments, with diagnostic tests confirming model validity.

The Monte Carlo framework introduced here, combined with component-based cost model and weather stratification, provides growers with probabilistic guidance rather than deterministic recommendations. Key insights include the following: (1) start DCA adoption with organic 'Gala' apples given favorable seasonal progression and minimal weather sensitivity; (2) focus on late-season storage (>6 months) when DCA advantages compound; (3) conduct orchard-specific performance and weather conditions assessments before scaling adoption, as location significantly affects outcomes; (4) consider weather sensitivity patterns when selecting cultivars and orchards for DCA implementation, given that 'Honeycrisp' shows reduced DCA dominance under harvest heat stress; and (5) implement portfolio approaches to manage downside risk, especially for weather-senstive cultivars and locations.

Despite these robust findings, the study was limited by its narrow geographic scope and the influence of unique climatic conditions. Future research should broaden geographic coverage, collect detailed facility-level cost data, examine consumer willingness to pay for DCA-preserved apples, and investigate the factors underlying orchard-level heterogeneity in weather sensitivity.

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