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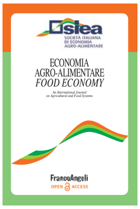

Assessing Agricultural Support Policy Impact through Traditional versus Machine-Learning Techniques

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Abstract

This paper analyses the impact of agricultural subsidies using traditional quasi-experimental research design that combines genetic matching procedure with regression analysis and causal forests, an adaptation of the random forest algorithm of Breiman (2001) for treatment effect estimation. The study is based on a structured orchard farm survey conducted in Albania, an EU candidate country. By employing both traditional and machine learning methods, the comparative methodological approach represents a notable contribution by enhancing the robustness of the findings, while highlighting the advantages of the random forest algorithm. The research results indicate that policy support significantly increased on-farm investments by approximately 4.7 million ALL (representing a 39% increase relative to the sample average investment for the analysed period), and direct apple revenues by about 2.48 million ALL (a 29% increase relative to the sample average revenue). Moreover, the policy had a substantial impact on altering the variety cultivation structure - beneficiary farmers replaced lower-quality apple varieties with higher-quality, market-demanded varieties, while non-beneficiaries showed no significant changes in their variety structure. As a result, the policy support enabled beneficiary farmers to better align their production structure with market demand, potentially boosting their future competitiveness.

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Introduction

Public transfers to agriculture have risen sharply: global support averaged USD 842 billion per year in 2021-2022 – more than twice the 2000-2002 level (OECD 2024). Albania, an emerging economy (the focus of this paper) follows this trend, albeit on a smaller scale. Under the Strategy for Agriculture, Rural Development and Fisheries (SARDF) 2021-2027, public appropriations reached EUR 90 million in 2023 (2.3% of national GVA) (Stojcheska *et al.*, 2024). Because the country is an EU-candidate state, evidence on the effectiveness of these transfers is indispensable for both domestic budget prioritisation and alignment with the Common Agricultural Policy (CAP).

Existing empirical findings on agricultural subsidies are heterogeneous. Subsidies and investment support for orchard farms can significantly improve farm productivity, income, and sustainability – because subsidies are associated with improved cultivars, high-density planting, integrated pest management, and precision agriculture (Ciaian *et al.*, 2015). In EU policy, there is broad consensus on the effects of subsidy types. Coupled payments, tied to output, can depress technical efficiency by distorting relative prices, whereas decoupled or investment-linked support can relax liquidity constraints and foster productivity growth (Latruffe and Desjeux, 2016; Latruffe *et al.*, 2017). However, in non-EU candidate countries the results are vaguely described. Effect magnitudes differ across countries, sectors, performance indicators and the temporal lag between investment and outcome. Short-term income effects may be limited, since orchards have long gestation periods. Problems of reverse causality are critical since larger, high incomes and capital endowed farms are also more able to acquire investments subsidies.

Methodological heterogeneity further clouds inference (Minviel & Latruffe, 2017). Most CAP appraisals still rely on simulation models or parametric regressions that are vulnerable to functional-form misspecification and selection bias (Colen *et al.* 2016). Quasi-experimental estimators – propensity-score matching, difference-in-differences, or instrumental variables – offer improvements, yet they remain sensitive to unobserved confounders or to data loss induced by pruning unmatched observations. Recent methodological advances, notably generalised random forests (GRF), allow causal estimation in high-dimensional settings with minimal parametric assumptions and explicit modelling of treatment-effect heterogeneity (Athey & Wager 2019). Applications of such machine-learning estimators in lower-income or pre-accession economies, however, are still limited.

The Albanian apple sector represents a suitable research setting. National apple output has expanded rapidly since 2010 owing to both area and yield gains. Production is concentrated in the high-altitude district of Korça, which contributes more than half of national supply and has a long tradition of commercial orcharding (Gerdoci *et al.*, 2015). Accelerated growth has exposed structural bottlenecks – outdated varietal structures, insufficient cold storage, and weak processing and export capacity. In response, the Ministry of Agriculture has operated a co-financed orchard-investment grant scheme that subsidises new plantings, varietal renewal, and on-farm cold rooms. The intervention is was expected to increase investments, adjust varietal composition towards market-preferred cultivars, and improve revenues and employment (AGT-DSA 2021). To date, no study has deployed causal inference techniques to verify these claims.

This study pursues two research objectives: first, it quantifies the causal impact of Albania's orchard-investment grants[1] on key apple-farm outcomes – capital investment, direct sales revenue, hired labour, and varietal composition – during the 2013-2018 programme period; second, it examines how the resulting effect estimates vary when calculated with a refined quasi-experimental estimator, genetic-matching regression, compared with those obtained via the state-of-the-art machine-learning algorithm, generalised random forest.

By addressing these objectives, the study (i) provides a rigorous evaluation of an agricultural investment programme in an EU-candidate country and (ii) offers empirical guidance on the relative merits of modern machine-learning techniques versus conventional matching estimators in mid-sized farm-survey settings.

Analysis relies on a cross-sectional survey of Albanian apple farms targeting both subsidies/programme beneficiaries (treated) and non-beneficiaries (controls) sampled from the same villages. Observable heterogeneity is mitigated through genetic matching, which iteratively searches for a weighting matrix that minimises multivariate imbalance. Post-matching least-squares regressions yield average treatment effects (ATEs). In parallel, causal forests recursively partition the covariate space and average treatment predictions over many trees; cross-validation determines optimal tuning parameters, and asymptotically valid standard errors enable inference. Analysing the two estimators highlights considerations related to bias control, efficiency, data utilization, and interpretability.

The rest of the paper is structured as follows, section 2 reviews the international literature on subsidy impacts and evaluation methods. Section 3 consists of methods including the econometric and machine-learning

1. Orchard investment grants correspond broadly to Investments in physical assets (Pillar II) of Common Agricultural Policy but is strictly related to grants for plantation of grafted seedlings of certified cultivars.

estimators. Section 4 presents ATE estimates and heterogeneous effects, juxtaposing the two methodologies. Section 5 discusses policy implications for Albania's CAP convergence and offers concluding remarks.

1. Literature Review Background

According to Kumbhakar and Lien, (2010) both coupled and decoupled subsidies can impact prices (and alter relative prices), incomes and labour, in turn affecting labour distribution and investment decisions, farm growth and income. Subsidies represent a stable source of farm income, since they are less variable than the other sources of income and contribute to higher farm income (Bojnec and Ferto, 2019). Subsidized investments in new orchards, especially those adopting modern cultivars and drip irrigation systems, tend to result in higher yields and better-quality output, leading to increased farm incomes (Ciaian *et al.*, 2015; Bartolini and Viaggi, 2013). Kirchweger *et al.* (2015) found no impact of Austrian agriculture subsidies on impact on revenues. In light of these mixed findings, it is relevant to examine whether, and to what extent, subsidies have influenced farm income in the context under study.

H1: *Subsidies positively impact farmers income.*

Support schemes may have a strong effect on farm investment. On one hand, increased and stable income coming from subsidies may encourage farmers to undertake investments (Gallerani *et al.*, 2008). Furthermore, investments subsidies such as plantation subsidies reduce entry barriers for perennial crops investments that are typically capital-intensive and risk-laden. They act as a "first-loss guarantee" – by covering a portion of upfront costs they encourage farmers to take the risk. Since in most areas, subsidies provided for plantation of orchards is carried in fallow land or land planted with annual crops, the incentive provided create additional multiplier effects: farmers are more likely to invest in complementary assets such as erosion control, support structures, irrigation systems, fencing, hail nets, and pest management systems. Reise *et al.* (2012) found that German farmers investment decisions are mainly driven by capital costs and the subjective perception of the risk resulting from the investment – only about half of the amount of the subsidy, is reflected in an increased willingness to invest (*ibid*). In the case of study, we expect that the subsidy should have an impact on investments, also given that they are provided as co-financing of investments.

H2: *Subsidies positively impact farm (current or planned) investments.*

Another area of interest is the impact of support schemes on employment. While about CAP effects there is a vast and contradicting literature (Olper *et al.*, 2012; Powell *et al.*, 2016; Petrick and Zier, 2012). Considering the differences in eligibility criteria and conditionalities, the investment subsidies may differ in terms of effect on family farm labour versus the paid labour (Bojnec and Fertő, 2022). While in plantation subsidies the need for labour increase (due to labour intensive starting process and increased need for pruning, spraying, thinning and harvesting) in investment subsidies lead to mechanization it can reduce the need for family labour. There is a scarcity of recent literature on the effect on labour. Further research is needed to assess whether, and to what extent, subsidy schemes have contributed to changes in farm employment in the context of this study.

H3: *Subsidies positively impact farm employment.*

EU CAP policies are found to have had a significant impact of farm size (Bartolini, and Viaggi, 2013). In non-EU countries investment grants may motivate farmers to convert fallow land to orchard land or even to lease or purchase neighbouring parcels – either temporarily (long-term leases) or permanently – thus increasing the operational farm size, even if legal ownership remains fragmented. Skreli *et al.* (2024) found that subsidy in the dairy sector results in increased flock size (increased production capacities). On the other hand, Skreli *et al.* (2015) and Gecaj *et al.* (2019), found that government subsidy scheme linked to investment (similar to the schemes which are subject of the analysis of this paper) had a clear net impact on increasing areas under perennial plantation in Albania. It is therefore relevant to examine whether investment support schemes have also contributed to an overall expansion of cultivated area.

H4: *Subsidies positively impact cultivated area.*

Subsidy investments in orchard farming play a crucial role in shaping varietal choices, often steering farmers toward commercially favoured, high-yield cultivars. However, when subsidy schemes are not inclusive of local or traditional varieties, there is high probability that these cultivars are abandoned or uprooted. These effects are already acknowledged in EU and globally (Hammel and Arnold, 2012). Farmers may obtain subsidies in the form of grants for seedlings, but only for improved or pure varieties (FAO, 2021). While during the early stages of post-communist development of the agriculture and rural development policies in Albania the focus was increasing cultivated area (production quantities), over the years, overproduction has increased the pressure to shift the focus toward quality. In the case of apple, there emerged the need to promote even substitute existing varieties with more market demanded varieties (Skreli and Imami, 2019). It is therefore of interest to assess, if or to what extent subsidies have contributed to changing/improving apple variety structure.

H5: *Subsidies impact apple variety structure (shifting to more market demanded varieties).*

2. Data and methods

The study draws on a structured face-to-face farm survey conducted in 2019 in Korca, the leading fruits/apple production region (as highlighted in the Introduction). The questionnaire was developed based on the literature review and semi-structured, in-depth interviews with value chain actors and sector experts carried out in 2018 and 2019. The sample universe consisted of all farmers who benefited from policy support during the period 2013-2018, while non-beneficiaries were randomly selected from the same villages where the beneficiaries were located.

The analysis of the impact of subsidy schemes in the apple sector is based on data from n = 244 apple farmers, 90 of whom have benefited from subsidy schemes during 2013-2018 and 154 have not benefited. Table 1 presents the main sample characteristics for the beneficiary and non-beneficiary groups. The shaded columns are the exploratory variables (i.e., variables used for matching), and the non-shaded columns are the outcomes of interests for assessing the impact.

The farmers' characteristics (covariates) used to create a homogenous group of farmers on observables include: farmers' age; household size; emigration (i.e. whether, there are emigrants in the family); household education level; farm/household agriculture land in ownership; (financial) record keeping and costs calculation (i.e. whether the farmers calculate production costs).

To assess the subsidy scheme impact two approaches are employed: causal forests and matching.

Causal effects are defined via the potential outcomes model (Imbens and Rubin, 2015): For each sample *i*, it is assumed that the potential outcomes $Y_i(0)$ and $Y_i(1)$ corresponding to the outcome we would have observed had we assigned control or treatment (W) to the *i*-th sample, and assume that we observe $Y_i = Y_i(W_i)$. The average treatment effect is then defined as $\tau = [Y_i(1) - Y_i(0)]$, and the conditional average treatment effect function is $\tau(x)=[Y_i(1) - Y_i(0)|X_i = x]$. In order to identify causal effects, we assume un-confoundedness (i.e., that treatment assignment is as good as random conditionally on covariates (Rosenbaum and Rubin, 1983).

Table 1 - Sample characteristics

Category (variable)	Beneficiaries (N = 90)		Non-Beneficiaries (N = 154)	
	Mean	Std.Dev	Mean	Std.Dev
Farmers' Age (years)	51.29	12.6	48.42	15.3
Farm size area (Ha)	25.78	24.64	18.62	16.3
Farmers' Education (years)	11.94	3.11	11.53	2.43
Household size	4.38	1.44	4.32	1.41
Keep notes & Calc. prod cost (yes/no)	28.0%	0.45	26.0%	0.44
Buyer – cold storage	37.0%	0.48	36.0%	0.48
Designated Successor (yes/no)	37.0%	0.48	26.0%	0.44
Revenue's apple (direct) (ALL)	11,123,946	11,040,887	7,005,715	8,115,956
Revenue's apple (indirect) (ALL)	17,151,567	30,924,866	9,766,672	11,166,596
Farm investment 2013-2018 (ALL)	16,974,444	22,320,603	8,861,779	16,538,388
Plans to invest in the next 5 years (ALL)	8,666,667	30,314,827	3,721,429	9,385,533
No Hired workers	6.21	5.89	4.03	4.84
Land area planted with apples (dynym)	16.27	20.54	10.72	6.96
Number of apple trees	2,184.91	2,721.41	1,193.56	1,357.98
Number of Starching trees	993.22	1350.05	487.11	620.6
Number of Reinet trees	34.5	177.32	9.61	37.43
Number of Ida red trees	107.11	201.17	123.61	264.49
Number of Granny smith trees	176.62	352.96	72.82	161.99
Number of Golden trees	399.57	1006.31	284.65	502.45
Number of Fuji trees	427.56	744.23	192.41	573.71
Number of other apple trees	46.33	166.8	23.34	113.87

Note: Dynym is 0.1 Ha; Y/N → the answer is a yes or no and the mean value shows the share of respondents that have answered yes; ALL → Albanian Lek (old format – has one more zero) – 1 EUR = 100 ALL (or 1000 Old ALL) (approximate average exchange rate during 2024)

In the first approach, the impact is evaluated with causal forests, which is an adaptation of the Breiman (2001) random forest algorithm for treatment effect estimation. Causal forest is a non-parametric method for heterogeneous treatment effect estimation that allow for data-driven feature selection while maintaining the benefits of classical methods, i.e., asymptotically normal and unbiased point estimates with valid confidence intervals (Athey, *et al.*, 2019). Its estimate can be thought of as an adaptive nearest neighbour method, where the data determines which dimensions are most important in selecting nearest neighbours. While classical methods such as k-nearest neighbours seek the k closest points to x according to some pre-specified distance measure (e.g., Euclidean distance), tree-based methods define closeness with respect to a decision tree, and the closest points to x are those that fall in the same leaf. The advantage of trees is that their leaves can be narrower along the directions where the signal is changing fast and wider along the other directions, potentially leading a to a substantial increase in power when the dimension of the feature space is even moderately large.

The causal forest estimation is done through the grf R package, which starts by fitting two separate regression forests to estimate $\widehat{m}(\cdot)$ (main effect function) and $\hat{e}(\cdot)$ (propensity function). It then makes out-of-bag predictions using these two first-stage forests and uses them to grow a causal forest (see Athey and Wager, 2019). The causal forest is trained and its parameters (e.g., min node size) are tuned by cross-validation (i.e., the parameters that minimize the objective function are selected). In addition, to improve precision as suggested by Athey and Wager (2019) first a pilot random forest is trained on all features (not all are presented here), and then a second forest is trained on only those features that saw a reasonable number of splits in the first step. Given good estimates of Y.hat and W.hat, this approach eliminates confounding effects (see Ertefaie (2018) for a further discussion).

In the second approach matching is used to match beneficiaries and non-beneficiaries on observables (see shaded area of table 1 for all covariates used in matching) to make them as similar as possible. In other words, to equate (or "balance") the distribution of covariates in the treated and control groups (See figure in Annex 1 for the covariate balance), so that the only thing that they would differ is treatment (benefiting from the subsidy). Then, to assess subsidy impact the average treatment effect (ATE) is estimated by regressing the treatment and covariates used during matching on the outcomes (see non shaded area of table 1 for descriptive statistics of outcome variables of interest).

On the other hand, the second estimation procedure of the impact of subsidy schemes that relies on matching employs genetic matching, which uses a search algorithm to iteratively check and improve covariate balance (see section 4.1 Sample balance and identification checks), and it is a generalization of propensity score and Mahalanobis Distance (MD) matching (Rosenbaum and Rubin 1985). It is a multivariate matching method that uses an evolutionary search algorithm aimed at maximizing the balance of observed covariates across matched treated and control units. (Diamond and Sekhon 2013). Then, to assess subsidy impact on an outcome the average treatment effect (ATE) is calculated by regressing the treatment and covariates used during matching on the outcome of interest on the matched data.

3. Results

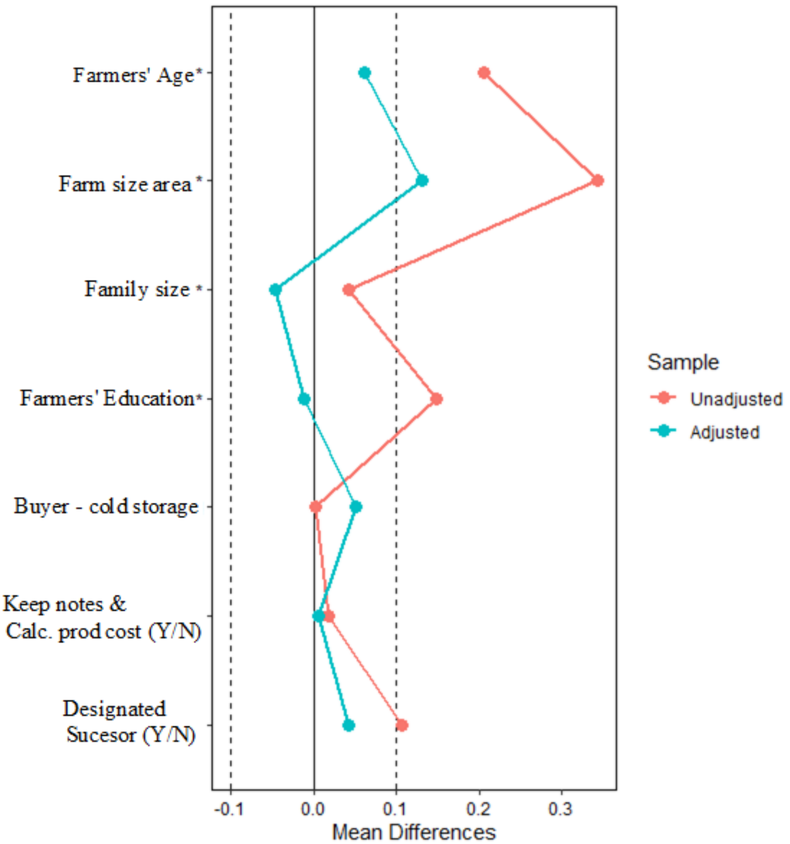
3.1. *Sample balance and identification checks*

Figure 1 plots standardised mean differences for every matching covariate before and after genetic matching. All covariates fall below the ± 0.10 threshold post-matching (aside farms size area, which is very close to the threshold), confirming that treated and control groups are comparable on observables. Multivariate imbalance (L1) drops from 0.889 to 0.735, and the share of observations inside common support rises from 6.8% to 17.6% (Table 2). These diagnostics support the un-confoundedness assumption.

Table 2 - Univariate imbalance measures

Category (variable)	**Type**	**Pre-Matching**		**After Matching**	
		Statistic	**L1**	**Statistic**	**L1**
Farmers' Age	(diff)	2.873	0.000	–0.245	0.000
Farm size area	(diff)	7.161	0.009	1.322	0.000
Farmers' Education	(diff)	0.412	0.019	0.000	0.000
Family size	(diff)	0.060	0.040	0.000	0.000
Keep notes & Calc. prod cost (Y/N)	(diff)	0.018	0.018	0.000	0.000
Buyer - cold storage	(diff)	0.003	0.003	0.000	0.000
Designated Successor (Y/N)	(diff)	0.107	0.107	0.000	0.000

Figure 1 - Covariate balance statistics



Note: Matched sample 98 of which 49 Beneficiaries and 49 non-Beneficiaries.

3.2. *Average treatment effects on investment, revenue and scale*

Table 3 compares average treatment effects (ATE) from the causal forest (CF) and genetic matching (GM).

H1: *Subsidies positively impact capital investment – Supported.*

Evidence shows that beneficiary farms invested significantly more than non-beneficiaries over the 2013-2018 period. The covariate balancing method (CF) estimates an average additional investment of ALL 4.70 million, which corresponds to a 39% increase relative to the sample-wide mean, and is statistically significant at the 10% level ($p < 0.10$). The generalized matching

(GM) estimate is slightly lower at ALL 3.63 million and not statistically significant at the 5% level, indicating some efficiency loss when unmatched observations are excluded. Nevertheless, both estimates suggest a positive and economically meaningful effect of subsidies on capital investment.

H2: *Subsidies positively impact farm income – Partially supported.*

The analysis reveals a positive effect of subsidies on direct apple revenue. The covariate balancing method (CF) estimates a statistically significant gain of ALL 2.48 million, equivalent to a 29% increase relative to the sample mean ($p = 0.037$), with a 95% confidence interval that excludes zero. The generalized matching (GM) approach yields a slightly larger estimate of ALL 3.42 million, though only marginally significant at the 10% level. However, when farm income is estimated indirectly through the price-quantity decomposition, the results are imprecise in both models, suggesting greater measurement error. Overall, the evidence provides moderate support for a positive income effect, particularly when using direct revenue data.

H4: *Subsidies positively impact cultivated area – Supported.*

Findings indicate that subsidies led to a measurable expansion in farm scale. Beneficiary farms increased their planted area by 3.0 dynym according to the covariate balancing method (CF, $p < 0.10$), and by 2.5 dynym under the generalized matching approach (GM, $p < 0.05$). Additionally, farms added approximately 600 apple trees (CF) and 535 trees (GM), with both estimates statistically significant at the 5% level. The consistency across models suggests that these changes reflect genuine scale enlargement, not just reallocation of existing resources, thereby confirming a positive effect of subsidies on cultivated area.

3.3. *Shifts in varietal composition*

H5: *Subsidies positively impact apple variety structure – Supported.*

The grant programme appears to have contributed to a shift toward more market-demanded apple varieties. According to covariate balancing (CF) estimates, there were statistically significant reductions in the share of ‘Idared’ (-4.8 percentage points) and ‘Golden’ (–8.3 pp), accompanied by a symmetric increase in ‘Fuji’ (+7.2 pp) – all significant at the 5% level. These varietal adjustments are consistent with the difference-in-differences comparison of varietal shares between 2013 and 2018. Although the generalized matching (GM) results confirm the same direction of change, the standard errors are larger, underscoring the greater precision and data retention advantage of CF. Overall, the results support the hypothesis that subsidies have influenced varietal upgrading in apple production.

Table 3 - Estimation of the ATE with causal forest and genetic matching approach

Category (variable)	**Causal Forest ATE & 95% CI**	**Genetic Matching ATE & 95% CI**
Revenue's apple (direct) (ALL)	2,480,202 +/– 2,288,947	3,420,673 +/– 3,850,755
Revenue's apple (indirect) (ALL)	4,139,887 +/– 5,686,389	10,002,284 +/– 13,74,7544
Farm investment 2013-2018 (ALL)	4,704,232 +/– 4,839,640	3,629,974 +/– 4,923,947
Plans to invest in the next 5 years (ALL)	5,049,054 +/– 7,031,487	1,148,768 +/– 2,237,387
Number of hired workers	1.292 +/– 1.33	1.409 +/– 2.098
Land area planted with apples (dynym)	2.957 +/– 3.502	2.501 +/– 2.029
Number of apple trees	599.537 +/– 528.59	534.851 +/– 446.112
Share of Starking to total apple trees	3.7% +/– 6.5%	2.6% +/– 4.9%
Share of Ida Red to total apple trees	–4.8% +/– 4.3%	3.4% +/– 2.8%
Share of Golden to total apple trees	–8.3% +/– 5.2%	–3.3% +/– 3.8%
Share of Granny smith to total apple trees	1.9% +/– 4.0%	–2.2% +/– 3.8%
Share of Fuji to total apple trees	7.2% +/– 6.3%	–0.7% +/– 5.1%
Share of Reinet to total apple trees	0.7% +/– 1.5%	0.2% +/– 0.8%
Share of the difference in number of Ida red 2018-2013 to total apple trees	–4.6% +/– 4.8%	0.2% +/– 1.5%
Share of the difference in number of Golden 2018-2013 to total apple trees	–1.0% +/– 3.0%	–5.1% +/– 3.2%
Share of the difference in number of Fuji 2018-2013 to total apple trees	5.3% +/– 4.3%	6.6% +/– 3.7%

Note: The outcomes in the green area are calculated by taking the difference in number of trees for the variety of interests between 2018 and 2013 divided by the number of apple trees in 2018.

3.4. *Employment effects*

H3: *Subsidies positively impact farm employment – Not supported.*

The evidence does not point to a strong or consistent employment effect. The covariate balancing method (CF) estimates a modest increase of 1.29 hired workers, which is marginally significant at the 10% level, but not at the more conventional 5% threshold. The generalized matching (GM) model shows a similarly sized increase (1.41 workers), though the estimate lacks statistical precision. These results, observed in a context of labour scarcity due to out-migration and ongoing mechanisation in the Korça region, are in line with mixed findings from the EU and point toward capital deepening rather than labour expansion as the primary adjustment channel.

4. Discussions and conclusions

This article assessed Albania's orchard-investment grant programme through two lenses: (i) its causal impact analysis on apple-farm performance during 2013-2018 and (ii) the comparative merits of two identification strategies – genetic-matching regression and the generalised random-forest (GRF) algorithm. Drawing on a survey of 244 farms in Korça and anchoring the analysis in the extensive subsidy literature, the section concludes by highlighting policy implications and study limitations.

The evidence confirms the study hypotheses. First, beneficiary farms realised a 39 % increase in capital outlays – comparable to the 20-35% uplift reported for Austrian "modernisation" grants (Kirchweger *et al.*, 2015) and to the credit-constraint relief observed under Ireland's decoupled payments (Toole & Hennessy, 2015).

Second, grants translated into a 29 % gain in direct sales revenue. The result converges with Gallerani *et al.* (2008), who found that orchard investments in Emilia-Romagna lifted gross margins once trees reached maturity, and is directionally opposite to Kirchweger *et al.*'s (2015) null revenue finding for annual-crop holdings – suggesting that perennial sectors capture investment returns more directly.

Third, the programme prompted structural upgrading, a marked shift away from 'Golden' and 'Idared' towards the higher-valued 'Fuji' (confirming H4 by demonstrating that targeted subsidies can influence product mix, not merely scale). This corroborates Skreli & Imami's (2019) qualitative diagnosis of cultivar mismatch and resonates with the CAP-driven varietal renewal documented for Italian and Spanish fruit farms (Gallerani *et al.*, 2008).

Employment effects were modest and statistically fragile, mirroring the mixed EU record, Olper *et al.* (2012) reported positive labour responses to

Pillar I transfers, whereas Powell *et al.* (2016) and Petrick & Zier (2012) found neutral or negative effects once mechanisation and rising wages were considered. In the context of relatively high labour abundance characterizing Albania during the time the survey was implemented, limited job creation should not be viewed as policy failure; rather, it can indicate capital-deepening association without extensive labour absorption (or with better utilization of household labour), as foreseen by Bartolini & Viaggi's (2013) model of structural change. Recent causal-forest evidence from Albania's dairy sector likewise detected no significant employment impact of coupled and headage payments (Skreli *et al.*, 2024).

Collectively, the results position Albania's orchard scheme within the mainstream of European evidence, it relaxes liquidity constraints, triggers productivity-oriented investments and nudges production towards higher market value, thereby supporting the income-stabilisation findings of Bojnec & Fertő (2019).

The comparison of genetic-matching regression with GRF provides new insights for impact evaluators. Both estimators confirmed the sign of programme effects, reinforcing internal validity. However, GRF yielded slightly larger investment impacts and smaller revenue impacts than matching. This divergence reflects their conceptual differences: matching minimises observable imbalance but trims observations outside common support, a weakness stressed by King & Nielsen (2019); GRF retains the full sample, captures high-order interactions and produces individualised treatment effects, in line with the robustness arguments of Athey & Wager (2019) and the consistency proofs of Wager & Athey (2018).

Our moderate sample size (n = 244) did not unduly penalise GRF – consistent with Scornet *et al.*'s (2015) claim that ensemble methods stabilise predictions in small datasets – but it did limit the granularity of heterogeneous-effect plots. In practice, GRF revealed that farms already keeping cost records captured the largest revenue gains, a nuance the matching model could not easily uncover. For policymakers planning performance-based disbursement, this level of detail is useful.

Looking ahead, policymakers can strengthen the programme on four fronts. First, tighten budget calibration and cross-compliance, keep the grant envelope healthy – perhaps even expand it – while tying future payouts to clear food-safety and environmental benchmarks that mirror upcoming CAP-2030 rules. Second, pursue integrated value-chain support: the shift toward higher-value cultivars will pay off only if growers also gain access to modern cold-storage and grading facilities, so new calls should pair orchard renewal with post-harvest investments. Third, broaden targeted advisory services, subsidising training in cost accounting and marketing could help smaller, less business-oriented producers catch up. Finally, it is important to make evidence-based improvements a regular part of monitoring to ensure that public funds are used as effectively as possible. This can be achieved by implementing the Farm Accountancy Data Network (FADN) in Albania, which remains one of the few countries in the region without such a system in place.

Despite these contributions, the study's inferences must be viewed in light of several manageable limitations, its cross-sectional design cannot eliminate all unobserved heterogeneity (DiPrete & Gangl, 2004); both estimators assume selection on observables, leaving room for hidden bias; the Korça-focused sample, while covering over half of national output, may not capture regional idiosyncrasies; the moderate sample size restricts very fine accurate subgroup analyses; and outcome variables exclude long-run yield, quality and profitability. Future panel data, broader geographic coverage, and administrative records will enable more robust cost-effectiveness assessments without compromising the advancements presented here.

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Annex

Table A1 - Univariate Imbalance Measures

	Type	Pre-Matching		After Matching	
		Statistic	**L1**	**Statistic**	**L1**
Farmers' Age	(diff)	2.873	0.000	–0.245	0.000
Farm size area	(diff)	7.161	0.009	1.322	0.000
Farmers' Education	(diff)	0.412	0.019	0.000	0.000
Family size	(diff)	0.060	0.040	0.000	0.000
Keep notes & Calc. prod cost (Y/N)	(diff)	0.018	0.018	0.000	0.000
Buyer - cold storage	(diff)	0.003	0.003	0.000	0.000
Designated Successor (Y/N)	(diff)	0.107	0.107	0.000	0.000

Note: Pre-Matching – Multivariate Imbalance Measure: L1 = 0.889, Percentage of local common support: LCS = 6.8%; After Matching – Multivariate Imbalance Measure: L1 = 0.735, Percentage of local common support: LCS = 17.6%.

Table A2 - Measure and objectives

Measure (CAP 2023-27 code)	Pillar	Key objective(s)
Coupled income support (CIS) – "Voluntary Coupled Support"	I	Prevent the **abandonment or decline** of sectors that are economically, socially or environmentally important but face structural difficulties, by boosting their **competitiveness, sustainability and/or quality**[2].
Decoupled income support – "Basic & complementary payments" (e.g., BISS, CRISS)	I	Provide a **stable income safety-net** and enhance **farm resilience**, while letting farmers follow market signals and deliver **public goods** (climate, environment, animal welfare) through reinforced conditionality[3].
Investments in physical assets	II	Improve the **economic and environmental performance** of holdings and processors, raise **resource-efficiency**, enhance **animal-welfare/food-safety**, and supply enabling infrastructure for agriculture and forestry[4].

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