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Exploring the Effects of Price Stabilization on Coffee Income Among Farmers in Rwanda: Does Certification Matter?

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Abstract

In recent years, farmers have faced growing exposure to economic shocks, extreme weather events, and conflicts, threatening their incomes, especially in developing countries. This study investigates whether voluntary sustainability standards help mitigate the economic impact of price shocks, using Rwanda's 2023 coffee price stabilization policy as a case study. Drawing on a panel of 834 coffee farmers, the study implements a difference-in-differences design with continuous treatment and household fixed effects, complemented by an instrumental variable strategy. Results show that the fixed-price regime reduced coffee revenues, but did not affect overall household income. Income diversification was used as a strategy to stabilize earnings, especially among non-certified farmers. Price premium from certification was insufficient to offset revenue losses. The findings highlight the need for policies that improve coffee sector profitability, secure stable premiums for certified farmers, and support income diversification to sustain rural livelihoods.

Keywords: Price stabilization, Coffee, Rwanda, Voluntary Sustainability Standards

JEL: Q12, Q18, Q13, L11

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1. Introduction

In recent years, farmers around the world have faced rising input costs driven by global crises such as the COVID-19 pandemic and the war in Ukraine (Arndt et al., 2023, Hebebrand and Debucquet, 2023). Since many of them rely on agricultural income to support their households, particularly in developing countries, they must find ways to maintain stable income amid such shocks. One immediate response is to raise the prices of their agricultural products. However, farmers often have limited bargaining power, especially in international markets where many cash crops are traded, and are therefore constrained in their ability to influence prices (Barrett, 2008). Additionally, restrictive price regimes can further limit their ability to adjust prices.

At the same time, several governments have introduced price stabilization policies to mitigate market volatility. Although existing evidence generally shows that price stabilization policies are often ineffective in achieving their intended outcomes (Newbery and Stiglitz, 1979, Jha and Srinivasan, 1999), and the welfare effects are usually heterogeneous (Bellemare et al., 2013, Mason and Myers, 2013), they may still benefit farmers by reducing uncertainty about expected returns and enabling more efficient production decisions (Myers, 2006).

At the same time, other strategies can be implemented concurrently to stabilize income. Understanding the interaction between price stabilization policies and these complementary strategies is essential to assess their overall impact on farmers' welfare. A long-term mechanism for improving income stability can be found in voluntary sustainability standards (VSS) (Bennett, 2018). Certified farmers, in fact, can receive a price premium on their products in return for meeting higher quality or sustainability requirements, acting like a private stabilization scheme.

This study explores the economic effects of a price stabilization policy on coffee farmers in Rwanda, focusing on their coffee revenues, total household income, and the role played by the certification schemes. Specifically, in 2023, the Rwandan government introduced a new pricing regime for coffee cherries, shifting from the previous flexible regime with a minimum price to a fixed price. In this context, certified farmers may have an advantage over non-certified producers due to the premium they receive. Under the new fixed price regime, the only way coffee washing stations (CWS) can offer higher payments to farmers is indeed by increasing the price premium. The study seeks to address the following research questions:

- How does the introduction of a price stabilization policy affect the income of coffee farmers?
- Does certification contribute to enhancing the resilience of coffee farmers' income in response to the change in the price regime?

Several studies have examined the impact of VSSs on coffee farmers in Africa, exploring various outcomes such as production, returns, income, poverty, and food security (Chiputwa and Qaim, 2016, Ruben and Hoebink, 2015, Vanderhaegen et al., 2018, van Rijsbergen et al., 2016). In Rwanda, Gather and Wollni (2022) investigated the relationship between Rainforest Alliance Certification and socio-economic and environmental outcomes, and the potential tradeoffs, finding positive associations with good agricultural practices and biodiversity-related practices but no significant economic effects. Other studies conducted in Rwanda explored the link between certification and agricultural practices (Elder et al., 2013) as well as socio-economic outcomes (Murekezi et al., 2012).

However, evidence on the effects of VSS in the context of shocks, and particularly on their interaction with public policies, remains scarce. To date, only Thompson et al. (2022) has explicitly examined whether VSS enhance the climate resilience of smallholders, using the case of Ghanaian cocoa. To my knowledge, no study has jointly evaluated public price stabilization measures and VSS participation. This study seeks to fill this gap by analyzing the relationship between certification and farmers' ability to cope with a price shock induced by a government-led price stabilization policy in Rwanda. In doing so, it provides novel evidence on how certification may influence resilience to market-related stressors.

The analysis provides valuable insights into the implications of price stabilization schemes for the income and welfare of coffee farmers. Furthermore, by examining the mechanisms through which certification might affect farmers' capacity to cope with such policies, the study aims to inform policymakers about the potential direct and indirect benefits of sustainability certification, supporting the design of more effective and equitable policy interventions.

The use of panel data represents a methodological improvement compared to previous studies based on cross-sectional data (Bacon, 2005, Beuchelt and Zeller, 2011, Weber, 2011, Ayuya et al., 2015, Chiputwa et al., 2015, Haggar et al., 2017, Tran and Goto, 2019, Gather and Wollni, 2022), as it allows for capturing dynamic effects and controlling for possible endogeneity issues arising from unobserved factors. A difference-in-differences (DiD) methodology with household fixed effects and continuous treatment is employed. An instrumental variable (IV) approach is applied to tackle possible endogeneity issues arising from side-selling.

Both the DiD and IV methods indicate that the change in the price regime negatively impacted coffee revenues, while it did not have a significant effect on total household income. A mediation analysis further reveals that the price stabilization policy prompted some farmers to diversify their income sources. Regarding the role of certification, the heterogeneity analysis shows no significant evidence that VSSs helped mitigate the negative effects of the price regime shift.

The paper is organized as follows. The next section describes the study background, providing details on the policy under analysis. Section 3 presents the theoretical framework the study is based on. Section 4 describes the data and presents some descriptive statistics. In Section 5, the methodology used to answer the research questions is explained. Section 6 provides and discusses the results of the analysis, and Section 7 concludes.

2. Study Background

Before every coffee harvesting season in Rwanda, the National Agency for the Development of Exports of Agriculture and Forestry (NAEB), acting on behalf of the Government of Rwanda, publishes the coffee farm gate price[1], which represents the minimum price at which coffee cherries must be purchased from farmers. This pricing mechanism allows for flexibility within certain boundaries. However, in February 2023, NAEB introduced a new pricing regime for the upcoming season, setting a fixed price of RWF 410[2] per kilogram of high-quality coffee cherries, consistent with the farm gate price of the previous year. If the classical price calculation had been used, the farm gate price would have been RWF 330 per kilogram of coffee cherries. NAEB's intention in changing the price regime was to prevent farmers from selling their coffee at excessively low prices. The introduction of a fixed price can be interpreted as a price stabilization policy that alters producers' exposure to market risk. Under risk aversion and in the presence of incomplete insurance and credit markets,

[1] Factors considered when calculating coffee farm gate price are costs of production, processing, and transportation, the coffee price at the New York commodities market, and exchange rates (Link)

[2] Source: https://twitter.com/RwandAgriExport/status/1628797502618058753/photo/1

such a policy can increase farmers' expected utility by reducing income variability (Newbery and Stiglitz, 1979). Because most production costs are incurred prior to the realization of market prices, the announcement of a fixed price before the harvest may also enhance allocative efficiency by enabling more predictable input and labor decisions. However, if the fixed is set too low to ensure adequate earnings, and if households face constraints in accessing alternative income-generating activities, such a policy may ultimately result in lower average returns and realized utility.

Evidence, as emerges from data collected in 2022, shows that coffee was generally sold at a higher price (RWF 587) than the farm gate price, as CWSs increased prices to attract farmers[3]. In addition, international coffee prices began to decline at the end of 2022, as shown in Figure 6 in Appendix 8.1. Under a flexible price regime, CWSs could face shrinking profit margins, limiting their ability to raise farm gate prices without risking a loss, since they may pay the farmers more than what they can receive from traders and exporters.

At the same time, the costs of inputs and food have escalated due to the Ukraine conflict and the COVID-19 pandemic. According to the National Institute of Statistics of Rwanda (NISR) data from February 2023, there has been an overall increase in the prices of food and non-alcoholic beverages by 60% between January 2022 and January 2023[4], with rural residents, including smallholder coffee farmers, experiencing the most substantial price hikes. Consequently, the fixed coffee price may

[3]It is important to note that Rwanda implemented a zoning policy in the coffee sector since 2016, requiring farmers to sell their coffee cherries to a designated CWS. However, this policy was only partially effective in practice. While farmers typically sold the majority of their production to their assigned CWS, some side-selling still occurred. As a result, CWSs were compelled to raise their prices to remain competitive.

[4]Source: https://statistics.gov.rw/publication/1911

not adequately account for the increased production costs. Given this situation, the ability to adjust coffee prices would enable farmers to offset the rising costs of other commodities. With the increased cost of consumer goods and relatively reduced income from coffee production resulting from the fixed pricing, the well-being of farmers is expected to decline.

Under these circumstances, certified farmers may have a relative advantage over non-certified producers due to the premium associated with certification. This premium, typically provided in cash, but sometimes in kind, represents the main economic benefit of certification. In a fixed-price regime, the primary way a CWS can offer better payments is by increasing this premium. To attract more farmers, certified CWSs are therefore likely to raise it, which in turn enhances the relative advantage of certified farmers.

Although the price premium can be embedded in the price farmers receive when selling coffee cherries, in Rwanda, it is typically paid as a separate bonus at the end of the harvest season. In the first round of data collection, certified farmers received a slightly higher average price than non-certified farmers, but the difference was not statistically significant. However, when the end-of-season premium is included, the difference becomes strongly statistically significant, despite the average premium amount being only 21 RWF. Notably, this additional premium is not exclusively tied to certification and can also be received by non-certified farmers. That said, only 8% of non-certified farmers received it in the first round, compared to 52% of certified farmers. Among those who received it, the average premium amount was the same for both groups. In the second round, the share of farmers receiving an additional premium increased for both groups: 28% among non-certified and 80% among certified farmers. This suggests that CWSs increasingly used the additional premium as a mechanism to supplement the fixed base price. Interestingly, while the average premium increased for certified farmers (from 31 to 46 RWF), it decreased for non-certified farmers (from 30 to 11 RWF).

Through these mechanisms, certified farmers are expected to experience a lesser adverse impact on their income compared to their non-certified counterparts in light of the changing price regime.

3. Theoretical Framework

The analysis is grounded in the microeconomic theory of commodity price stabilization. Research on the welfare effects of price stabilization schemes dates back to the early 20th century, when Keynes first advocated for price controls as a means to prevent excessive price fluctuations. Later, Newbery and Stiglitz questioned the overall desirability of such interventions (Kanbur, 1984). Turnovsky (1976) concluded that the welfare gains from price stabilization depend on the elasticity of supply, while Schmitz et al. (1981) highlighted that they also depend on the degree of production diversification. In this study, I link this literature to the VSS by adding the price premium component in the utility maximization function and exploring how the combination of price stabilization and price premium affects supply elasticity and income diversification across certified and non-certified farmers.

Although studies on price stabilization in low-income countries often rely on the agricultural household model (Singh et al., 1986), in which households act as both producers and consumers, as for instance in Barrett (1996) and Bellemare et al. (2013), this framework is not appropriate in the context under analysis. Coffee is not typically consumed by farmers in Rwanda, but it is rather produced almost exclusively for sale to the CWSs. I therefore adopt a pure producer model, treating households solely as profit-maximizing agents responding to market incentives. Consistent with this approach, utility is defined in terms of revenues and income, rather than consumption or expenditure. The farmer chooses inputs L,F, and K to maximize economic utility, subject to a budget constraint, as follows:

$$\max_{L,F,K} \; [P(\mathbb{R}) + \delta] \cdot Q$$

$$\text{s.t.} : L + F + K \leq \bar{I}$$

where:

- $Q = f(L, A, F, Z)$: Production function, where L = labor, A = land, F = fertilizer and other inputs, and Z = household/farmer characteristics. A is assumed fixed in the short run.

- $\mathbb{R} \in \{\text{flexible}, \text{fixed}\}$: Price regime indicator.

- $P = \begin{cases} P^M : \text{Market-determined} & \text{if } \mathbb{R} = \text{flexible} \\ P^F : \text{Fixed price} & \text{if } \mathbb{R} = \text{fixed} \end{cases}$

- δ: Price premium for certification.

- $\delta = \begin{cases} > 0 & \text{if farmer is certified} \\ 0 & \text{if farmer is not certified} \end{cases}$

- K: capital needed for investments, such as machinery and other agricultural equipment.

- $\bar{I}$: total available budget

When the outcome is the total household income, an additional factor w, which represents a vector of other income sources, is added to the direct utility function, following Myers (2006), as follows:

$$\max_{L,F,K} \; [P(\mathbb{R}) + \delta] \cdot Q + w$$

The model does not incorporate credit and insurance markets, as coffee farmers in Rwanda typically lack access to such markets. Storage is also not included in the model, as farmers have to deliver coffee cherries to the CWS within a few days after harvesting.

In a dynamic model, I adapted the model by Myers (2006) to consider households only as producers. At time t=0, households have the following expected utility:

$$E_0 = \sum_{t=1}^{T} \beta^t \max_{L,F,K} \; [P_t(\mathbb{R}) + \delta_t] \cdot Q_t + W_t$$

Where β^t denotes the preference discount factor, and $W_t = w_t - m$. The term m captures the deviation between the expected coffee income, based on the farmer's usual earnings, and the currently anticipated coffee income. If we define $Y^* = (P_t^* + \delta_t^*)\cdot \mathrm{Q}_t$ as the initial coffee income, based on the initial levels of price and premium, m= Y_t-Y^*. It represents the compensatory adjustment required to maintain the same level of total income as in the baseline period. The parameter m may take positive or negative values and reflects a distributional reallocation across income sources. A negative m indicates that expected coffee income has declined, prompting the household to shift resources toward alternative income-generating activities included in W.

The price of cash crops such as coffee is typically determined on international commodity markets. Under a flexible pricing regime, where the only constraint is a minimum threshold represented by the farm gate price, an increase in international demand can incentivize traders and exporters to pressure CWSs to raise the prices they offer to farmers in order to secure larger volumes. This market dynamic allows farmers to sell their coffee cherries at prices above the official farm gate price.

While farmers are price takers and are expected to sell exclusively to designated CWSs under the zoning policy, price variations across CWSs indicate that the policy was not strictly enforced, enabling farmers to partially choose higher price offers. The internal competition among CWSs can create tensions under fluctuating international conditions. If global demand falls, leading to a decline in the international market price P^I, traders and exporters may face a situation in which domestic prices,driven by local competition, exceed the export price. In such cases, enforcing a fixed domestic price P^F below P^I would actually benefit traders and exporters by preserving their margins.

It is important to note that under a flexible price regime, the coffee price becomes known to farmers only after the harvest. Consequently, production decisions regarding inputs, labor, and capital must be made based on expected rather than actual prices. Given that the New York commodities market price, used to calculate the farm gate price, was declining, farmers operating under ($\mathbb{R}$ = flexible) would have made production decisions in anticipation of relatively low prices.

A policy-induced price shock that imposes a fixed price insulates domestic producers from international market fluctuations and may lead to a more efficient allocation of resources. However, if the fixed price (P^F) is set below the level that would have prevailed under market conditions (P^M), farmers' net incomes decline and may even turn negative if unit production costs exceed the fixed price. In recent years, Rwanda has faced substantial increases in input prices due to broader macroeconomic pressures, further eroding potential profits from coffee cultivation.

Under such circumstances, it may become economically rational for farmers to reduce or cease coffee production and reallocate labor and capital toward alternative income-generating activities, either on- or off-farm.

Certified farmers may be partially protected from adverse price effects through the premiums offered by certified CWSs. These premiums can increase total coffee revenues, although their effectiveness ultimately depends on the magnitude of the premium. If a farmer is certified and the CWS offers a premium δ, this amount is added to the price term in the farmer's utility function. However, in Rwanda, the price premium is typically distributed at the end of the agricultural year, after the harvest season has concluded. Consequently, even under a fixed price regime, certified farmers face uncertainty regarding the exact amount they will receive. By contrast, non-certified farmers can more easily assess ex ante whether coffee production remains profitable, assuming other yield-determining factors remain constant, and may choose to allocate resources toward alternative crops or income-generating activities that are expected to yield higher returns.

4. Data and descriptive statistics

The study uses longitudinal data collected from 834[5] farmers belonging to 39 CWSs in 5 districts[6] of Rwanda. The first round of data, which serves as the baseline, has been collected from October 2022 to February 2023. The second round was collected in the same period in 2023/2024. Among the farmers interviewed in

[5] 8 farmers could not be interviewed in the second round of data collection, resulting in an attrition rate of 0.95%.

[6] Rusizi, Nyamasheke, Karongi and Rutsiro in the Western Province, and Huye in the Southern Province.

2022/2023, 61% are certified (516)[7], of which more than half have the Rainforest Alliance certification (266), while the other 250 have other certifications (Organic, Fairtrade, and Café Practises).

For the outcomes of the analysis, two measures are considered: annual coffee revenues and per capita total household income.

Income is defined as the gross per capita daily income and is computed as the sum of annual earnings from agricultural production, both crop and livestock, as well as on-farm and off-farm labor wages, remittances, and other income sources. Since only information on the most productive coffee plot was collected, income from coffee production can be underreported when the farmer has more than one plot. As a robustness check, the analysis is conducted for the subsample of farmers with only one coffee plot. Coffee revenues include the earnings of coffee sold and the premium received. Revenues are defined on an annual level and refer to the latest harvest season.

Table 1 presents descriptive statistics for the variables used in the analysis, including outcome variables, coffee price, and control variables.

The data reveal a significant reduction in coffee revenues during the second round. However, households managed to maintain a constant level of total income over time, suggesting that they adopted coping strategies to generate income from other sources. One potential strategy could be income or crop diversification (Myers, 2006). The decline in coffee production during the second round can be attributed to a reduction in productivity, given that 2023 was an "off-year" within the country's biennial coffee

[7]Please notice that the sample was intentionally designed to over-represent certified farmers and is therefore not representative of the broader population of coffee farmers. For a detailed description of the sampling design, please refer to Paz et al. (2024).

Table 1: Descriptive statistics.

Variable	**Pooled**	**2022/2023**	**2023/2024**	**Mean diff.**
Outcome variables				
PC daily income	635	658	611	
Coffee revenues (000)	343	431	255	***
Log(PC daily income)	-1.06	-0.99	-1.12	**
Log(Coffee revenues)	5.29	5.61	4.97	***
Treatment and IV				
Coffee price (RWF/Kg)	518.6	587.5	449.7	***
Price premium (RWF/Kg)	36.8	30.8	40.8	***
N. farmers in CWS	825	844	806	*
Control variables				
Farmer is certified	0.61	0.61	0.61	
N. Coffee trees	360	380	340	
TLU	1.09	1.13	1.05	*
Simpson index for income	0.40	0.38	0.42	***
Simpson index for crop prod.	0.28	0.26	0.30	***
Farming time (hours)	3.86	3.97	3.76	
Hired labor	0.86	0.90	0.82	***
Coffee produced (Kg)	633	714	552	***

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Mean values are reported, with standard deviations in parentheses. Monetary values are expressed in RWF. CWS capacity is proxied by the quantity of coffee bought by the CWS. The median capacity is computed as the median quantity of coffee bought by the other CWSs in the same sector or district. TLU stands for Tropical Livestock Units. Simpson index for income is computed over monetary values, while the index for crop production considers quantity of crop produced. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

production cycle, or to a switch towards other crops or income activities. Specifically, farmers may have responded to the lower coffee prices and reduced profitability by intensifying the production of other crops and/or other income-generating activities. In fact, the Simpson's Diversity Index[8] shows an increase in income source and crop production diversities in the second round. Both increases are statistically significant.

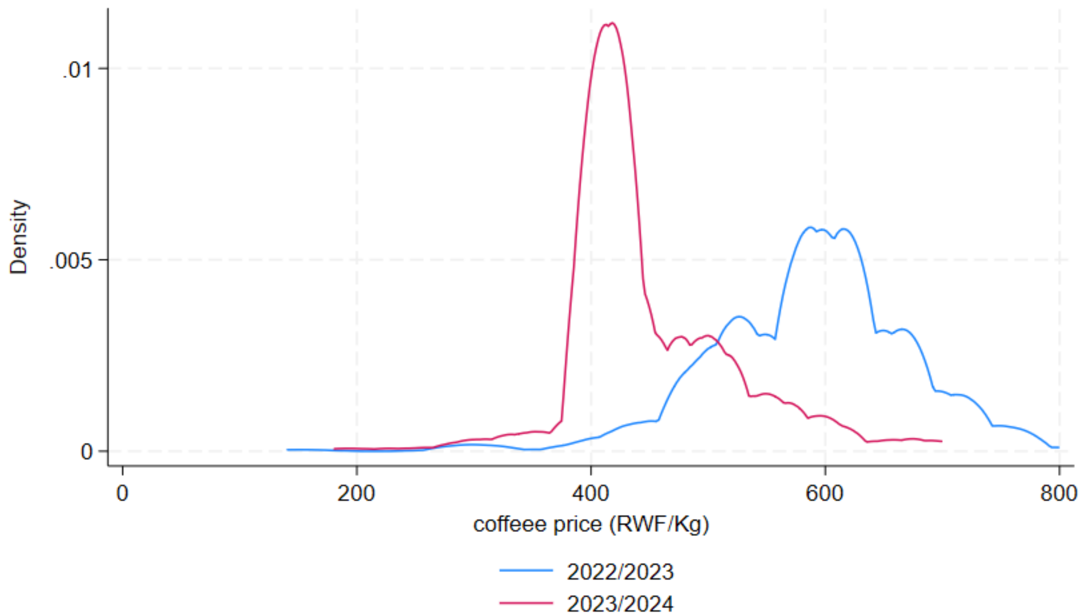
As expected, coffee price drastically reduced after the change of the price regime, moving from 587 RWF/kg on average in the first round to 450 RWF/Kg in the second round, as reported by farmers. The median price reported a similar shift, with a 180 (110) RWF reduction in the second round, as shown in Figure 1. At the same time, the share of certified farmers receiving a price premium increased from 48% in 2022 to 68% in 2023. The average amount also rose slightly, although, as shown in Figure 7 in Appendix 8.1, it was too small to represent a significant deviation from the base price.

The coffee price decrease was indeed perceived as the main shock occurred on the coffee plot, with more than 50% of the farmers interviewed in the second round saying that the reduction significantly affected their coffee production. The reduction in coffee price, together with the increase in agricultural input prices, show the highest increase in the second round as compared to other shocks experienced on the coffee plot, as reported in Figure 2.

A similar result is observed when considering any shock experienced by the households in the last year. Specifically, 74.8% of households reported experiencing rising prices, particularly for food products, while 43.9% indicated a decrease in coffee prices. These were the two most frequently reported shocks, as reported in Figure

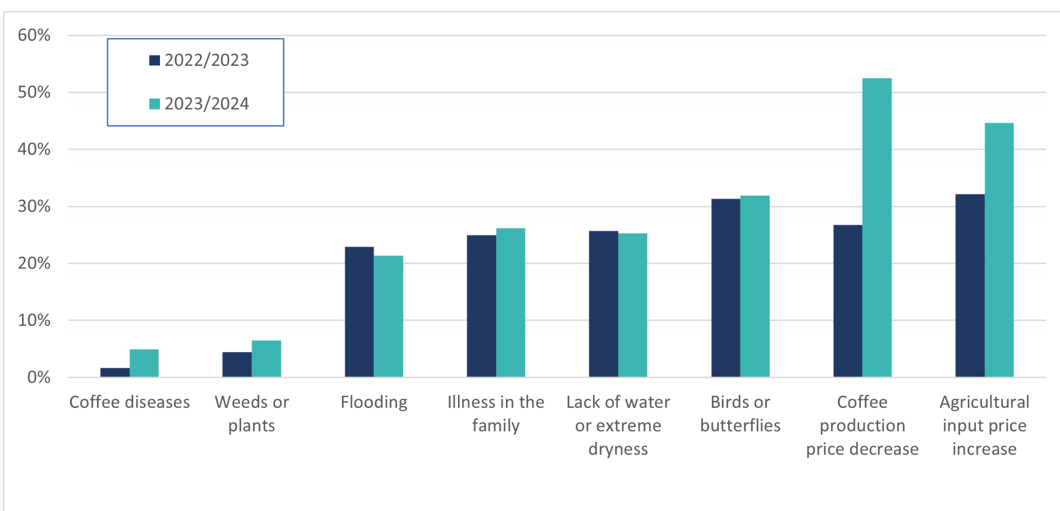
[8]The index measures the complement of dominance and ranges between 0 and 1, with higher values for greater diversity.

Figure 1: Coffee price over rounds



Source: author's elaboration.

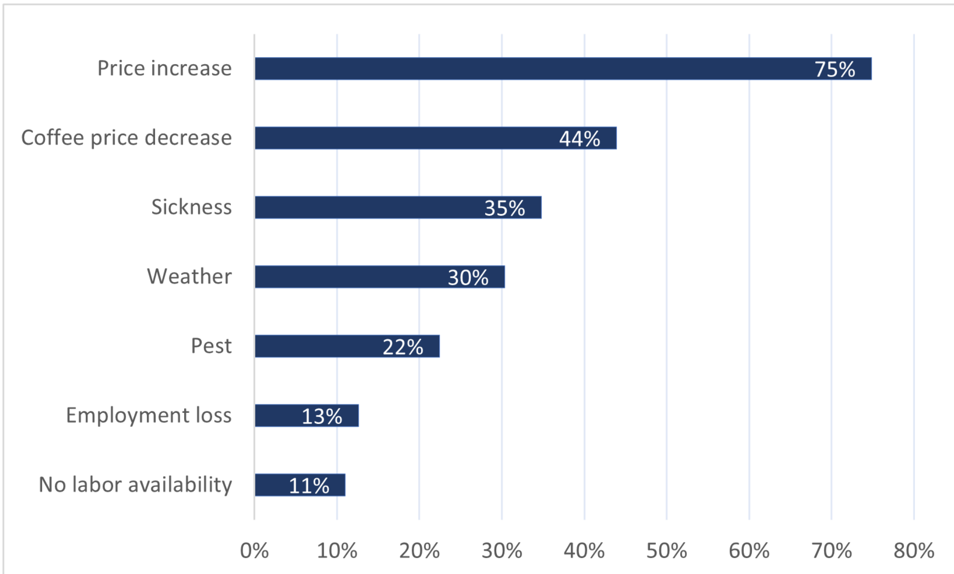
Figure 2: Shocks experienced on the coffee plot, by round.



Source: author's elaboration.

3. Meanwhile, the premium saw a slight increase during the second round, likely as a compensatory measure for the price reduction, as shown in Table 1.

Figure 3: Shocks experienced by the household in 2023.



Source: author's elaboration.

5. Methodology

I use a DiD design with household fixed effects and a continuous treatment where the treatment is the difference in the price across the two years. As the change in the price regime affected all farmers, I do not have defined treatment and control groups. However, farmers who were receiving a higher price in the first round will be affected more by the change. I can then use the difference in price between the two rounds to measure the exposure to the policy and the intensity of the effect. The use of a continuous variable is required because only 7% of the sample reported a non-negative change in price in the second round, so a dummy equal to 1 if the difference in price is negative, and zero otherwise, is not possible, as I would not have enough observations in the control group.

The equation of the ATT is specified as follows:

$$y_{ht} = \alpha_h + \lambda_t + \beta_1(Price\Delta_h * Post_t) + \beta_2 Controls_{ht} + \epsilon_{ht} \tag{1}$$

Where y_{ht} is the economic outcome of household h at time t, either total income or coffee revenues[9]; α_h and λ_t capture household and time fixed effects to control for time-invariant unobserved heterogeneity and the within-group variation over time, respectively; $Post_t$ is a dummy equal to 1 for the second round, and 0 for the first round; $Price\Delta_h$ is the change in price, which corresponds to the treatment variable. The variable is computed as the inverse of the difference between the price in 2023 and the price in 2022; β_2 is the coefficient of the interaction term between coffee price and time. Finally, a set of time-varying controls is included, such as farming time, hired labor, TLU, Simpson index for income and crop, number of coffee trees in the plot, quantity of coffee produced, while ϵ_{ht} is the error term.

I first included the change in the coffee price and the change in the additional premium as two separate variables in the model, to disentangle the corresponding effects. I subsequently included the premium in the calculation of the treatment variable for the rest of the analysis. I would expect that the premium plays a more relevant role in the second round, as it is the only tool CWS can use to increase the price.

The main assumption of DiD is that the treated and control groups show parallel trends in the outcome variable prior to policy implementation. Although it is possible

[9] Coffee revenues are computed by multiplying the price by the quantity of coffee produced. The price includes the additional premium.

to test for parallel trends even with continuous treatment, as outlined in Callaway and Sant'Anna (2024), I do not have pre-2022 data to verify this assumption.

As an alternative method, I use Double/Debiased Machine Learning (DDML) for DiD, which offers a more flexible and robust approach than traditional DiD models. DDML relaxes the global parallel trends assumption by conditioning on covariates using machine learning. This allows for more credible identification under conditional parallel trends, especially in high-dimensional settings. However, DDML still relies on the validity of the parallel trends assumption, albeit in a weaker, conditional form. It is also more robust to the curse of dimensionality, which can render traditional nonparametric estimators inefficient when dealing with numerous observed covariates. By leveraging machine learning to flexibly control for confounders and model treatment effect heterogeneity, DDML improves the accuracy and credibility of causal estimates (Ahrens et al., 2024). Additionally, DDML is more robust to model misspecification due to its use of orthogonal score functions, making it particularly valuable in complex settings where standard DiD assumptions are hard to justify (Chernozhukov et al., 2018). However, it doesn't deal with unobserved confounding beyond what the covariates can control for.

This would not be a problem if I was sure that the treatment is exogenous and assigned randomly. However, one potential concern is the endogeneity of the price change variable arising from omitted variable bias, represented by side-selling in the first year. Although farmers generally lack the bargaining power to set coffee prices and are expected to sell all their production to the assigned CWS under the zoning policy, side-selling to other CWSs offering better prices may still occur when the zoning policy was in place. Due to the fear of side-selling, CWSs may increase prices, while side-selling itself directly influences farmers' revenues and incomes. Consequently, CWSs are likely to determine their prices based on the market competition.

This would explain why average prices in 2023/2024 were above the farm gate price. Since side-selling is unobservable, and at the same time it is not controlled by the fixed effects as it is expected to vary over time, an instrumental variable (IV) approach is implemented as an alternative model.

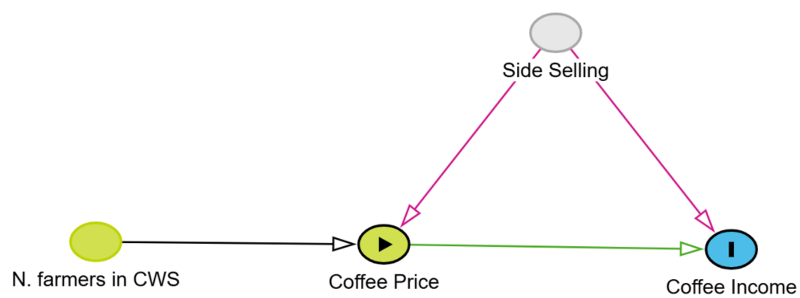
A plausible instrument is the market power[10] of the CWSs. Greater buyer power reflects weaker competition among CWSs and is therefore associated with the ability to offer lower coffee prices (satisfying the correlation with the endogenous regressor), while it should not directly affect farmers' income or coffee revenues except through prices (satisfying the exclusion restriction).

The rationale is that greater market power strengthens the CWS's bargaining position over farmers, reducing competition among CWSs and creating monopsony-like conditions. Given that coffee cherries require processing within hours of harvest, competition among CWSs is effectively limited to those located nearby (Macchiavello and Morjaria, 2020). I proxy market power using the number of farmers supplying each CWS in 2022. Because the distribution of farmers was determined by the zoning policy, based on geographic proximity rather than endogenous factors such as market preferences or farmer characteristics, a higher number of suppliers signals that the CWS dominates its catchment area, enabling it to offer lower prices. A potential concern is that side-selling could increase or decrease the number of farmers belonging to each CWS, introducing a reverse correlation between the omitted factor and the instrument. However, these additional farmers are not reflected in the official statistics reported by CWS managers, as disclosing such information would imply a violation of the zoning policy. This interpretation is consistent with previ-

[10]It is not possible to use the median price of the other CWSs, as it is correlated with the outcome variable, since it affects farmers´ decision on where to side-sell.

ous studies showing that greater competition among CWSs is associated with higher prices (Macchiavello and Morjaria, 2020). It is also supported by descriptive statistics. Relevance is supported by a statistically significant correlation of -0.16 (p = 0.001) between the instrument (number of farmers) and the endogenous regressor (price change). Regarding the exclusion restriction, the instrument displays no association with the outcome variables (household income and coffee revenues) once price changes are controlled for[11] The causal relationship of the IV is described in Figure 4.

Figure 4: Directed acyclic graph of instrumental variable causal relationship.



Source: author's elaboration using DAGitty v3.1.

As an additional robustness check, I conducted a falsification test using dependent variables that should not be affected by the policy in the short term. The results, reported in Appendix 8.5, show no significant effects and thereby further support the validity of the identification strategy.

I then computed a heterogeneity analysis to see if being certified[12] played a role in

[11] This is the result of a OLS with the number of farmers and the price change as regressors.

[12] The variable of certification is equal to 1 if the farmer belongs to a CWS that was certified in

the effect of the change in price regime. The corresponding equation is the following:

$$\begin{aligned} y_{ht} = \alpha_h + \lambda_t + \beta_1(VSS_h * Post_t) + \beta_2(Price\Delta_h * Post_t) \\ + \beta_3(VSS_h * Price\Delta_h * Post_t) + \beta_4 Controls_{ht} + \epsilon_{ht} \end{aligned} \tag{2}$$

With regards to certification, a common challenge in evaluating the effects of various sustainability standards is the potential endogeneity of certification status, as discussed in Elliott (2018). While the study emphasizes the importance of using methods to address selection bias of certification adoption, such as matching techniques, as in Gather and Wollni (2022) and Becchetti et al. (2012), or instrumental variable approaches, as in Akoyi and Maertens (2018), Sellare et al. (2020), and Knößlsdorfer et al. (2021), it also highlights the critical role of context. In Rwanda, certification operates under unique circumstances. The decision to adopt certification is made by the coffee washing station (CWS), not the individual farmer.

Given this policy framework, certification can be considered exogenous at the farmer level. However, it can be endogenous at the CWS level. To control for this, I computed inverse probability weights (IPW) based on observable CWS characteristics and implemented a weighted regression when investigating the role of certification. Regression details for the IPW estimation are reported in Appendix 8.3.

2022, and zero otherwise. This way, the variable is constant over time and is captured by farmer fixed effects. 3 CWSs changed their certification status in 2023. However, I expect that the effect of this change is not immediate. As a robustness check, I computed the same heterogeneity analysis with the certification status of each year.

6. Results

The results of the analysis confirm some of the trends observed in the descriptive statistics. Both the DiD and IV estimates suggest that the change in the price regime had a negative effect on coffee revenues. However, total household income does not appear to have been affected by the policy shift. To better understand this finding, I conducted a mediation analysis to explore the mechanisms households employed to maintain their income levels despite declining coffee revenues. In particular, I examined income diversification strategies, as outlined in the conceptual framework. The mediation analysis shows that, as a consequence of the price regime change, some farmers, especially non-certified ones, diversified into other income sources.

Regarding the role of certification, the heterogeneity analysis finds no significant evidence that voluntary sustainability standards helped mitigate the negative effects of the price regime shift. This may be due to the relatively low premium received by certified farmers in Rwanda. Although the premium increased slightly from 2022 to 2023, it was likely insufficient to offset the drop in coffee prices.

6.1. Difference-in-difference

Table 2 presents the results of the DiD estimation for per capita income and coffee revenues, both in logarithmic form, with and without household fixed effects. In this model, coffee price and premium are kept separate. The findings indicate that changes in the price regime had a significant impact on coffee revenues. The negative coefficient suggests that a 1 RWF decrease in the coffee price is associated with a 0.18% decline in coffee revenues. When accounting for household fixed effects, the coefficient slightly reduces. Assuming a linear effect, an average price reduction of 137 RWF translates to a 20.4% drop in coffee revenues.

Conversely, overall household income does not appear to be significantly affected by the price change. This may be explained by households reallocating income from other sources as a coping strategy to smooth their level of total income. Indeed, diversification, both in terms of income sources and to a lesser extent of crops, is positively and significantly associated with household income.

The change in the premium instead does not report any significant effect. This can be due to the small amount of the premium, which was not enough to have an impact on both total income and coffee revenues.

The time trend reveals a decline in coffee revenues over time, with the reduction being more pronounced when household fixed effects are included. VSSs positively influence both outcome variables in the OLS model.

Among the other control variables, the quantity of coffee produced has a positive effect on both outcomes, as expected. When accounting for household fixed effects, hired labor and the n. of coffee trees show a positive and significant effect on coffee revenues.

Table 3 presents the results when incorporating the price premium into the calculation of price difference. I would expect the premium to offset the impact of the price regime change, resulting in no significant effect on either outcomes. However, the estimates show minimal differences compared to the previous models. The coefficients and significance levels for total income remain almost unchanged. The coefficient of price change on coffee revenues when including premium is slightly smaller than when accounting only for the change in coffee price, and it is still statistically significant at the 0.001 level. This suggests that the price premium was not effectively leveraged to mitigate the negative effects of the price reduction caused by the regime change. When accounting for the price premium, a 137 RWF decrease in the coffee price is associated with a 17.5% reduction in coffee revenues.

Table 2: Diff-in-diff - Pooled OLS and FE.

	DiD		DiD with FE	
	Log (Income)	Log (Coffee Rev.)	Log (Income)	Log (Coffee Rev.)
ΔCoffee price	7.03e-05	0.00148***		
	(0.000292)	(0.000202)		
Post	-0.0336	-0.213***	-0.0700	-0.267***
	(0.0629)	(0.0445)	(0.0639)	(0.0476)
Post#ΔCoffee price	-0.000512	-0.00178***	-0.000482	-0.00167***
	(0.000368)	(0.000250)	(0.000365)	(0.000252)
ΔPremium price	-0.000116	0.000925**		
	(0.000574)	(0.000380)		
Post#ΔPremium price	0.000342	-0.000598	0.000521	-0.000458
	(0.000908)	(0.000526)	(0.000922)	(0.000531)
VSS	0.0945*	0.141***		
	(0.0503)	(0.0376)		
N. coffee trees	0.000159***	3.98e-05	3.15e-05	0.000214**
	(5.34e-05)	(7.84e-05)	(0.000102)	(0.000103)
TLU	0.0593**	0.0724***	0.0392	0.0259
	(0.0252)	(0.0176)	(0.0353)	(0.0235)
Simpson index for income	0.960***	0.176*	1.028***	0.204*
	(0.130)	(0.0920)	(0.159)	(0.107)
Simpson index for crop	0.574***	0.0850	0.334**	-0.0302
	(0.105)	(0.0773)	(0.143)	(0.0952)
Farming time (hours)	-0.0108	0.00777	-0.00583	0.00509
	(0.00716)	(0.00473)	(0.0103)	(0.00648)
Hired labor	0.311***	0.470***	-0.0152	0.178**
	(0.0669)	(0.0601)	(0.101)	(0.0831)
Coffee produced (Kg)	0.000524***	0.000855***	0.000488***	0.000725***
	(5.23e-05)	(8.24e-05)	(5.76e-05)	(8.49e-05)
Constant	-2.334***	4.049***	-1.862***	4.720***
	(0.0976)	(0.0817)	(0.126)	(0.101)
Observations	1,667	1,667	1,667	1,667
R-squared	0.365	0.648	0.212	0.595

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Standard error clustered at the household level. Post is a dummy equal to 1 for the year 2023/2024. Coffee price change and premium change are inverted. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

In the rest of the analysis, I consider the price change that includes the premium.

Table 3: Coffee price and premium comparison.

	Coeff.	Robust Std. Err.	t	P>t	[95% conf. interval]	
ATT						
Log(Income)						
ΔCoffee price	-0.00048	0.000365	-1.31	0.192	-0.00119	0.00024
ΔCoffee Price + ΔPremium	-0.00049	0.000341	-1.43	0.153	-0.00116	0.000181
Log(Coffee Rev.)						
ΔCoffee price	-0.00172	0.000252	-6.82	0.000	-0.00221	-0.00122
ΔCoffee Price + ΔPremium	-0.00141	0.000234	-6.03	0.000	-0.00187	-0.00095

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Standard error clustered at the household level. Coffee price change and premium change are inverted. Control variables, time and household fixed effects included.

I then computed the ATE using DDML using a partially linear model, where the controls enter through the unknown and potentially nonlinear function g_0. The key assumption is conditional orthogonality, namely E{Cov(U, D— X)} = 0 (Ahrens et al., 2024). The estimation of the coefficient β_1 of the interaction between the difference in price and the post dummy is conducted via a two-step procedure: first, the conditional expectation of Y (outcome) given X (control variables) and of D (price change) given X are estimated. Second, Y and D are residualized by subtracting their respective conditional expectation function (CEF) estimates, and the resulting CEF residuals of Y are regressed on the CEF residuals of D.

Results presented in Table 4 confirm the previous findings. The reduction in the price of coffee cherries had a negative effect on coffee revenues but did not significantly affect total household income. While the impact on coffee revenues remains negative and statistically significant when using DDML, both the magnitude and significance level are slightly reduced as compared to previous models.

Table 4: DDML results.

	Coeff.	Robust std. err.	z	P>z	[95% conf.	interval]
Dep. Variable: Log(Coffee revenues)						
ΔCoffee Price*Post	-0.00053	0.000241	-2.19	0.029	-0.001	-5.5E-05
_cons	0.004766	0.016456	0.29	0.772	-0.02749	0.037018
Dep. Variable: Log(PC daily income)						
Δ Coffee Price*Post	-0.00041	0.000315	-1.31	0.191	-0.00103	0.000206
_cons	-0.00223	0.02191	-0.1	0.919	-0.04517	0.040714

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Robust standard error. Coffee price includes premium. The price change is inverted. Control variables, time and household fixed effects included.

6.2. Instrumental variable approach

In this section, I use an instrumental variable approach to offset possible endogeneity issues. The first-stage regression shows that the instrument significantly predicts the endogenous variable, with a coefficient of -0.038, which is strongly significant (p-value = 0.000), as reported in the first-stage regression results in Table 5.

The key diagnostic statistic for instrument validity is the first-stage F-statistic, which tests the weak identification and rejects the null that the instrument and the treatment are not correlated. The Cragg-Donald Wald F statistic is 20.14, and the Kleibergen-Paap F statistic is 24.27, both above the rule of thumb threshold of 10 and above the Stock-Yogo critical values[13]. The Kleibergen-Paap rk LM statistic is 23.41 with p-value = 0.0000, rejecting the null hypothesis of underidentification.

Table 5: First stage - IV approach

	Coeff.	Robust Std. Err.	t	P>t	[95% conf. interval]	
Instrument= N. of farmers in 2022	-0.0383	0.0078	-4.93	0.000	-0.05361	-0.02306
N. coffee trees	-0.0190	0.0086	-2.21	0.027	-0.03589	-0.00214
TLU	-3.2168	3.9929	-0.81	0.421	-11.0546	4.621076
Simpson index for income	34.2755	14.7041	2.33	0.020	5.412344	63.13868
Simpson index for crop	-31.3745	14.5558	-2.16	0.031	-59.9465	-2.80245
Farming time (hours)	1.6165	0.9305	1.74	0.083	-0.20993	3.442959
Hired labor	16.8280	9.7096	1.73	0.083	-2.23125	35.88719
Coffee produced (Kg)	0.0033	0.0037	0.87	0.383	-0.00407	0.010591
Constant	159.0834	7.4133	21.46	0.000	144.5316	173.6352

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Standard error clustered at the household level. The dependent variable is the change in coffee price and premium. Variables expressed in first difference, except the instrument.

The second-stage regression results, reported in Table 6, confirm that the price change negatively impacted both income and coffee revenues. As in the previous model, only the coefficient for coffee revenues is statistically significant. The effect on coffee revenues when accounting for endogeneity is larger (0.38%) than the previous estimates. This implies that a 137 RWF price reduction would result in a 40.9% decline in coffee income.

[13] At 10% maximal IV size, the critical value is 16.38

Table 6: Second stage - IV approach

	Log(Income)	Log(Coffee rev.)
ΔPrice and premium	-0.00281	-0.00384**
	(0.00219)	(0.00156)
N. coffee trees	-8.50e-06	0.000178
	(0.000116)	(0.000109)
TLU	0.0268	0.0217
	(0.0357)	(0.0257)
Simpson index for income	1.097***	0.262**
	(0.187)	(0.129)
Simpson index for crop	0.258	-0.0990
	(0.166)	(0.113)
Farming time (hours)	-0.00125	0.00947
	(0.0115)	(0.00770)
Hired labor	0.0470	0.204**
	(0.109)	(0.0930)
Coffee produced (Kg)	0.000495***	0.000731***
	(6.04e-05)	(8.71e-05)
Constant	0.226	-0.0174
	(0.276)	(0.199)
Observations	809	809
R-squared	0.153	0.341

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Standard error clustered at the household level. Coffee and premium price change is inverted. Variables are in first difference. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

6.3. Heterogeneity analysis: Role of certification

Table 7 shows the results of the model with IPW and household fixed effects[14] for income and coffee revenues, to explore the role of certification in mitigating the negative effect of the price difference in the post-intervention.

For income, no statistically significant effects were found. In contrast, for coffee revenues, the coefficient for the post-intervention period is negative and statistically significant, indicating a decline in coffee revenue after the price regime change. A significant negative interaction between coffee price changes and the post-intervention period further indicates that coffee revenues decreased as price differences increased during this time.

The combined effect of certification and post-intervention is not statistically significant, suggesting that certified households did not experience a different change in coffee revenues compared to non-certified households. Similarly, the triple interaction term is not statistically significant, implying that certification did not alter the relationship between price changes and coffee revenues differently during the post-intervention period. This suggests no differential impact of certification in the post-period across varying price changes.

[14]The model was also estimated without fixed effects, yielding similar results. Furthermore, to address potential bias from controls that might be correlated with certification status, which could act as bad controls and affect the effect of certification on the outcome, the same models were run without control variables. These estimations also produced similar results.

Table 7: Heterogeneity analysis - Diff-in-diff with FE and IPW.

	Log (Income)	Log (Coffee Rev.)
Post	-0.0986	-0.243***
	(0.112)	(0.0650)
VSS#Post	0.0413	-0.135
	(0.135)	(0.0891)
Post#ΔPrice and premium	-0.000213	-0.00180***
	(0.000672)	(0.000366)
VSS#Post#ΔPrice and premium	-0.000406	0.000676
	(0.000807)	(0.000501)
Constant	-1.846***	4.727***
	(0.143)	(0.104)
Controls	yes	yes
FE	yes	yes
Observations	1,667	1,667
R-squared	0.216	0.591
Number of uniqueid_n	834	834

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

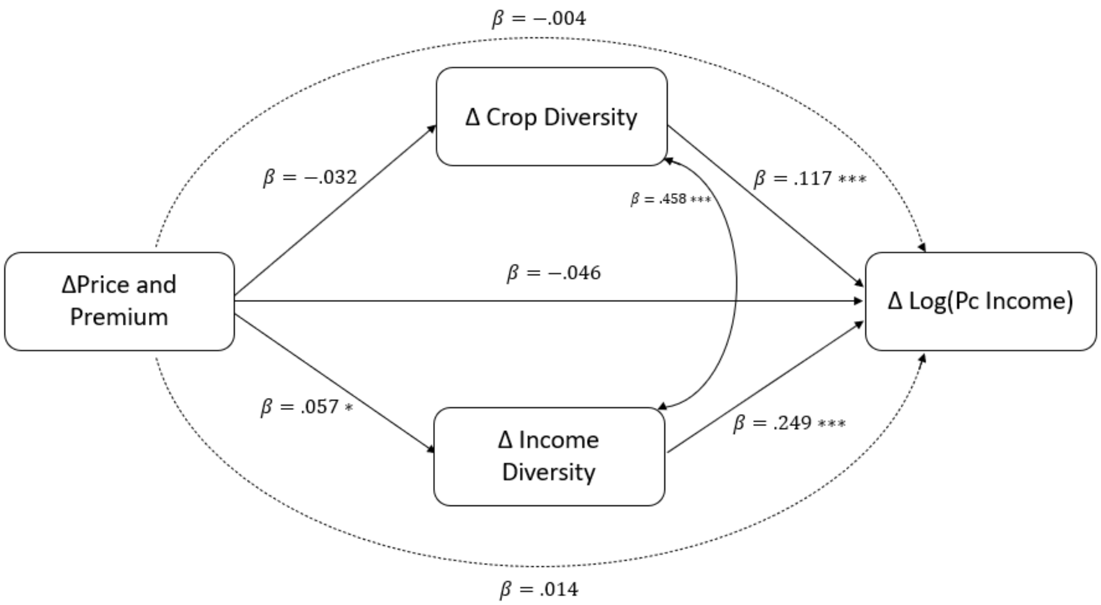
Note: Standard error clustered at the household level. Post is a dummy equal to 1 for the year 2023/2024. Coffee price change is inverted. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

6.4. Diversification as a coping mechanism

Figure 5 presents the results of the mediation analysis conducted over the full sample. The diagram reports the direct and indirect effects of the price change on per capita income, with crop and income diversification acting as mediators[15].

[15] The mediation analysis is conducted using structural equation models. Results of tests for the goodness of fit of the model over the entire sample are the following: Chi-square=30.110 with p-value=0.001; RMSEA=0.049; CFI=0.949; TLI=0.893; SRMR=0.031; CD=0.132.

Figure 5: Mediation path - Per capita income



Source: author's elaboration.

Note: Standardized coefficients. Standard error clustered at the household level. Household fixed effects applied. Post is a dummy equal to 1 for the year 2023/2024. Coffee price change is inverted. Error terms of crop diversity and income diversity variables have been correlated to improve the model fit, as suggested by modification indices. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Both income and crop diversification contribute positively to income growth. For the full sample, the price change does not appear to have directly influenced crop diversification, and it shows a weak positive association with income diversification. The overall indirect effect of the price change mediated by income diversification is indeed positive but not statistically significant. However, when disaggregating by certification status, I observe that non-certified farmers responded to the price reduction by increasing their income diversification. Table 8 reports the results of the mediation analysis conducted separately for the subsamples of certified and non-certified farmers.

Table 8: Mediation analysis - direct and indirect effects.

	Certified farmers	Non-certified farmers
Direct effects		
Log(Income)		
ΔPrice	-0.0614	-0.0384
Income div.	0.1986***	0.2995***
Crop div.	0.1212**	0.1582***
Income div.		
ΔPrice	-0.0072	0.1791***
Crop div.		
ΔPrice	-0.0543	0.0579
Indirect effects		
Log(Income)		
ΔPrice via income	-0.0014	0.0536**
ΔPrice via crop	-0.0066	0.0092

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Robust Standard error. Inverse probability weights applied for the certified and non-certified subsamples. Standardized coefficients reported. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

This finding suggests that non-certified farmers were able to adjust more flexibly to the price change by reducing coffee production and shifting to alternative income sources. This interpretation is further supported by the analysis of supply elasticity. When estimating the price elasticity of coffee supply in the second round separately for certified and non-certified farmers, I find that non-certified farmers exhibit a positive and statistically significant elasticity, whereas certified farmers display a negative and insignificant one. The difference in elasticities between the two groups is statistically significant (p = 0.024), indicating that certification dampens farmers' responsiveness to price changes. In other words, certified farmers' production decisions appear less sensitive to price fluctuations, while non-certified farmers adjusted their supply more rapidly in response to the policy-induced price change. Details of the elasticity analysis are provided in Appendix 8.4.

When exploring the price change effect on the different income sources, I find that non-certified farmers managed to offset the reduction in coffee income due to the price shift by increasing agricultural wage income and production from other crops. Certified farmers instead moved to other income sources, primarily receiving social transfers in the second round[16].

[16] However, it must be noticed that the number of observations reporting an amount of income from other sources among certified farmers is very limited (22 farmers in the first round, and 7 farmers in the second round). Therefore, this result should be interpreted with caution.

Table 9: Income sources.

	Certified farmers							Non-Certified farmers						
	Coffee	Other Agriculture	Ag. Wage	Livestock	Non-ag. Wage	Remittances	Other	Coffee	Other Agriculture	Ag. Wage	Livestock	Non-ag. Wage	Remittances	Other
Post	-0.355***	0.250*	-0.243	0.262	0.358	0.308***	-0.265***	-0.301***	-0.0719	-0.419	0.446	0.231	0.226*	-0.0613
	(0.0703)	(0.151)	(0.249)	(0.210)	(0.222)	(0.116)	(0.0989)	(0.0731)	(0.183)	(0.309)	(0.299)	(0.517)	(0.123)	(0.145)
Post*Price	-0.000953***	-0.000988	0.00177	-0.00186	-0.00188	-0.000465	0.000926*	-0.00121***	0.00210*	0.00320*	-0.00297*	-0.00221	-0.000327	5.95e-05
	(0.000348)	(0.000926)	(0.00133)	(0.00131)	(0.00133)	(0.000694)	(0.000486)	(0.000431)	(0.00112)	(0.00172)	(0.00166)	(0.00271)	(0.000711)	(0.000826)
Constant	4.905***	1.449***	1.595***	0.451	0.366	-0.498**	0.292**	4.804***	0.301	1.239*	-0.521	0.0316	-0.0870	-0.139
	(0.148)	(0.332)	(0.548)	(0.507)	(0.485)	(0.208)	(0.126)	(0.158)	(0.410)	(0.744)	(0.521)	(0.619)	(0.156)	(0.177)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1,021	1,021	1,021	1,021	1,021	1,021	1,021	646	646	646	646	646	646	646
R-squared	0.554	0.467	0.183	0.236	0.093	0.076	0.049	0.526	0.547	0.178	0.248	0.130	0.064	0.030
Number of uniqueid_n	511	511	511	511	511	511	511	323	323	323	323	323	323	323

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Standard error clustered at the household level in parentheses. Inverse probability weights applied for the certified and non-certified subsamples. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

7. Conclusions

This study contributes to the broader literature on price stabilization policies and VSS by examining their combined effects on farmers' economic welfare. Specifically, I analyze a policy-induced price shock, the 2023 coffee price stabilization policy introduced by the Rwandan government, and its interaction with certification schemes among coffee farmers. Economic welfare is proxied by coffee revenues and total household income.

As emphasized by Bellemare et al. (2013), linking price volatility/stability to household welfare requires a clear, rigorous strategy and adequate household-level and price data that properly capture the commodity under analysis and the local context. By exploiting the change in Rwanda's coffee price regime and drawing on unique primary panel data collected among coffee farmers, this study offers novel empirical evidence on how public price policies and private certification mechanisms jointly shape farmers' resilience to market shocks.

The policy under analysis presents a significant identification challenge, as it affected all farmers simultaneously, leaving no untreated comparison group. To address this limitation, the identification strategy relies on a continuous treatment framework with household and time fixed effects, complemented by the use of an instrumental variable to address potential endogeneity. Employing multiple model specifications and estimation methods further enhances the robustness and credibility of the findings.

The findings indicate that the shift led to lower coffee revenues. A 137 RWF drop in the average coffee price, which accounts for the price premium, resulted in a 20.4% decline in revenues under the DiD model with FE, with estimates ranging between 7% and 41% across specifications. In response, coffee farmers, especially non-certified ones, have turned to engaging in additional income-generating activities to sustain their livelihoods. The mediation analysis confirms that diversification of income sources has been used by non-certified coffee farmers as a coping mechanism to keep stable levels of income.

As emphasized by Gilbert (1986) and Turnovsky (1976), assessing the effects of price stabilization policies requires considering the distribution of welfare gains across different actors in the value chain. In the Rwandan coffee context, although the effects on CWSs and traders remain uncertain, the evidence presented here clearly indicates that the 2023 price stabilization policy did not benefit farmers.

Given that coffee is a key cash crop in the country, contributing 11 percent of agricultural exports, the government should implement policies that enhance coffee production profitability and make the sector more economically attractive to farmers.

VSS could, in principle, mitigate negative price shocks through premium payments. Evidence on the economic benefits of VSS is extensive, generally indicating positive or neutral effects on producers' welfare, although substantial variation exists across contexts, particularly with respect to institutional settings (Meemken, 2020). The findings of this study are consistent with the broader literature, showing no significant difference when the premium is included in the price computation. This likely reflects the fact that, in Rwanda, the 2023 premium amount was insufficient to offset the decline in coffee prices. The heterogeneity analysis further shows that certification alone does not appear to mitigate income or revenue losses, highlighting the need for complementary measures to enhance the effectiveness of certification schemes.

Finally, as shocks experienced by farmers become more frequent and severe, it is crucial to broaden this line of research to assess the role of VSS under conditions of crisis. This study provides one of the few empirical contributions in this direction, but further research is required to determine whether VSS can effectively function as a mechanism to enhance producers' resilience and to identify the conditions under which they can fulfill this role.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this proposal, the author utilized ChatGPT to enhance the spelling, grammar, and clarity of the paper. Following the use of this tool, the author thoroughly reviewed and edited the content as necessary.

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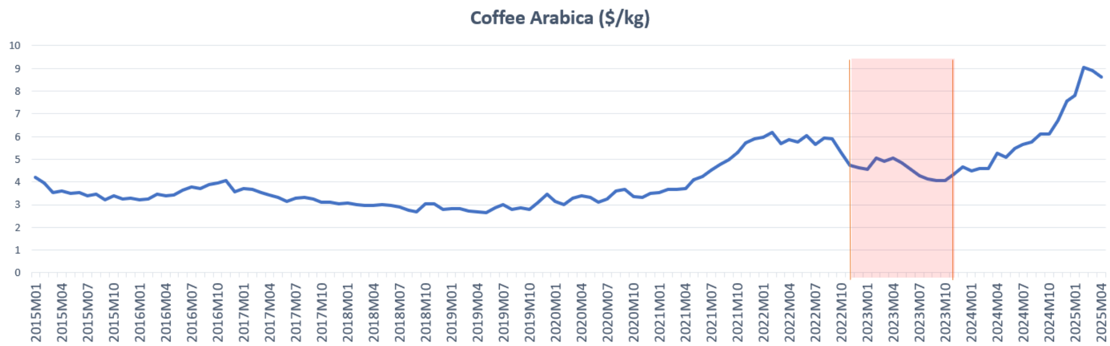
8. Appendix

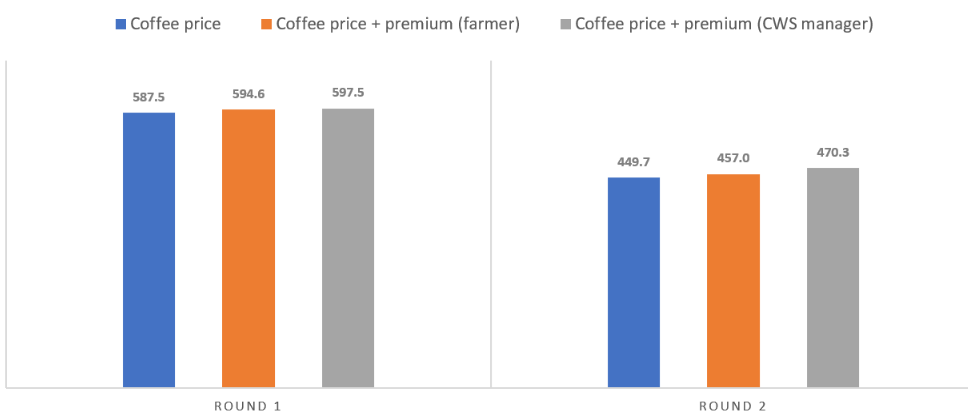
8.1. Supplementary Descriptive Figures

Figure 6: Monthly Price of Coffee Arabica, in nominal USD.



Source: author's elaboration from the World Bank Commodity Price Data. Available at https://www.worldbank.org/en/research/commodity-markets. Accessed on May 05, 2025. *Note:* the 2023 year is highlighted in red.

Figure 7: Price comparison with and without premium



Source: author's elaboration. *Note:* Farmer´s premium is the price premium per Kg reported by each farmer. Instead, the manager´s premium is the price premium reported by the CWS manager.

8.2. Full regression tables

Table 10: Diff-in-diff - Full regression table.

	Log(Income)		Log(Coffee Rev.)	
	(1)	(2)	(3)	(4)
Post	-0.0654	-0.0689	-0.269***	-0.326***
	(0.0633)	(0.0591)	(0.0475)	(0.0439)
Post#ΔCoffee price	-0.000476		-0.00172***	
	(0.000364)		(0.000252)	
Post#(ΔCoffee price+ΔPrice premium)		-0.000488		-0.00141***
		(0.000340)		(0.000234)
N. coffee trees	3.04e-05	3.13e-05	0.000214**	0.000223**
	(0.000102)	(0.000102)	(0.000103)	(0.000104)
TLU	0.0391	0.0392	0.0271	0.0281
	(0.0354)	(0.0352)	(0.0233)	(0.0235)
Simpson index for income	1.030***	1.029***	0.197*	0.179*
	(0.159)	(0.158)	(0.107)	(0.107)
Simpson index for crop	0.336**	0.334**	-0.0266	-0.0233
	(0.143)	(0.143)	(0.0953)	(0.0962)
Farming time (hours)	-0.00592	-0.00582	0.00494	0.00455
	(0.0103)	(0.0103)	(0.00649)	(0.00653)
Hired labor	-0.0125	-0.0150	0.180**	0.166**
	(0.100)	(0.100)	(0.0820)	(0.0818)
Coffee produced (Kg)	0.000488***	0.000488***	0.000721***	0.000720***
	(5.73e-05)	(5.76e-05)	(8.45e-05)	(8.54e-05)
Constant	-1.865***	-1.863***	4.711***	4.726***
	(0.126)	(0.126)	(0.100)	(0.101)
Observations	1,667	1,667	1,667	1,667

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Standard error clustered at the household level. Post is a dummy equal to 1 for the year 2023/2024. Coffee price change and premium change are inverted. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

8.3. Inverse probability weights

Inverse probability weights are computed to balance certified and non-certified farmers. A logit model based on the first-round of data[17] is used to predict the probability that a CWS is certified. The regression includes observable CWS-level characteristics, such as manager attributes (age, sex, and education) and structural characteristics (cooperative status and presence of at least one international buyer). From the estimated propensity scores, I calculated the inverse of the predicted probability for certified farmers (treated group) and the inverse of one minus the predicted probability for non-certified farmers (control group), which are then used as weights in the main analysis. The results of the logit regression are reported in Table 11.

Table 11: Logit regression to compute inverse probability weights.

	CWS is certified
CWS is a Cooperative	2.164***
	(0.219)
Education of CWS manager	-0.183***
	(0.0562)
Age of CWS manager (years)	0.0202**
	(0.00938)
CWS manager is female	-1.481***
	(0.241)
At least one international buyer	0.363**
	(0.164)
Constant	2.018*
	(1.030)
Observations	834

Source: Authors' elaboration based on 2022/2023 data.

Note: Robust Standard error in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

[17] The CWS-level dataset is based on recall information collected in 2024/2025.

8.4. Supply elasticity

To examine whether certified and non-certified farmers differ in their production responsiveness to changes in coffee prices, I estimate a supply elasticity model using a log–log specification with an interaction between log price and certification status. Results from the regression (Table 8.4) indicate a negative elasticity for certified farmers. The average marginal effects report a positive and statistically significant elasticity for non-certified farmers: a 1% increase in the coffee price is associated with a 0.58% increase in production ($p = 0.039$). In contrast, the estimated elasticity for certified farmers is negative and statistically insignificant (–0.22%, $p = 0.302$), suggesting no detectable supply response to price changes. The interaction term between log price and certification status is statistically significant ($p = 0.024$), and a formal Wald test confirms that the elasticity differs between certified and non-certified farmers ($p = 0.024$). These results imply that certified farmers are not able to adjust their coffee production in response to short-run price fluctuations, whereas non-certified farmers show a positive and significant supply response.

When performing the same elasticity analysis using data from the first round, I do not find any statistically significant differences between certified and non-certified farmers. This suggests that differences in supply responsiveness emerge only after the policy change, rather than reflecting pre-existing differences in production behavior.

Table 12: Supply elasticity from log-log regression in 2023/24.

	Log(Coffee Kg)
Log(Coffee price)	0.537**
	(0.262)
VSS	4.573**
	(2.014)
VSS#Log(Coffee price)	-0.746**
	(0.329)
N. coffee trees	0.000854***
	(0.000151)
TLU	0.0860***
	(0.0322)
Simpson index for income	0.600***
	(0.185)
Simpson index for crop	0.207
	(0.130)
Farming time (hours)	0.0268***
	(0.00980)
Hired labor	0.698***
	(0.0942)
Constant	1.109
	(1.599)
Observations	834
R-squared	0.331

Source: Authors' elaboration based on 2023/2024 data.

Note: The variable of coffee price includes premium. Robust standard error in parentheses.

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

8.5. Falsification Test

As a robustness check, I conduct a falsification test using outcomes that should not be affected by the price stabilization policy. Specifically, I estimate the DiD model with FE using two variables, asset index and household size, neither of which is expected to respond to short-term price changes in the coffee sector. As shown in Table 13, both specifications yield statistically insignificant estimates, as expected. These results support the validity of the identification strategy and provide further reassurance that the main findings are not driven by spurious correlations or unobserved shocks unrelated to the policy.

Table 13: Diff-in-diff - Other dependent variables.

	Asset index	HH size
Post	0.0675	-0.0294
	(0.0895)	(0.0768)
Post#(ΔCoffee price+ΔPrice premium)	-0.000332	-0.000662
	(0.000547)	(0.000445)
N. coffee trees	0.000408	-0.000180
	(0.000279)	(0.000168)
TLU	0.0668	0.0305
	(0.0697)	(0.0698)
Simpson index for income	0.416*	-0.0757
	(0.217)	(0.221)
Simpson index for crop	0.531**	-0.0449
	(0.222)	(0.204)
Farming time (hours)	0.00402	0.0125
	(0.0158)	(0.0114)
Hired labor	-0.0296	-0.0218
	(0.138)	(0.131)
Coffee produced (Kg)	0.000268*	1.91e-05
	(0.000141)	(7.30e-05)
Constant	-0.707***	5.014***
	(0.220)	(0.175)
Observations	1,667	1,667
R-squared	0.053	0.013
Number of uniqueid_n	834	834

Source: Authors' elaboration based on 2022/2023 and 2023/2024 data.

Note: Standard error clustered at the household level. Post is a dummy equal to 1 for the year 2023/2024. Coffee price is inverted and include premium. Significance levels: *** p<0.01, ** p<0.05, * p<0.1