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Heterogenous effects of milk price volatility on French dairy farms economic viability: roles technological equipment uses

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Abstract

In a context of increased milk price volatility and dairy farm modernization, our study aims to shed light on whether the costs associated with the financial investments made when acquiring technologies and their maintenance costs exacerbate the damage suffered when the price becomes volatile, or whether the expected productivity gains actually help to cope with this market hazard. To do this, we distinguish three farm categories according to three separate variables that approximate the level of technological tools used. Then, we estimate the variation in the level of viability of each group when price volatility changes.

We apply fixed effect ordered logistic regression on data gathered from the French farm accountancy data network from 2002 to 2020. Sample is divided into three categories according to their levels of intensification and use of technological tools. We estimated separately the viability models of each category to check for heterogeneity.

Our results show positive roles of low intensification and moderate use of technological equipment in mitigating the impact of an increase of milk price volatility on dairy farm viability. These contribute to provide insights on farmers' coping strategies effectiveness and the extent to which modernization is advantageous.

Keywords

economic viability, feologit, milk price volatility, technological tools

Presenter Profile

Marie Rose Randriamarolo-Malavaux is the research project manager of the agricultural risk management Chair, located in Beauvais France. She is specialised in vulnerability, risk and risk management analysis. Her doctoral thesis was focused on dairy farms' milk price volatility management which include the presented article.

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Introduction

Ensuring economic viability constitutes a prerequisite of farm sustainability (O'Donoghue et al., 2016) because not only, a persistent low viability leads to the abandonment of activities (Barnes et al., 2020); but also, good viability encourages the takeover of farms by younger generations (Farrell et al., 2021).

It is acknowledged that risks, such as commodity price volatility, significantly threaten the farm economic viability (Vrolijk et al., 2010), but to our knowledge, studies quantifying the severity of these impacts are rare. Dervillé & Fink-Kessler (2019) highlighted, via a comparative case study, strategies allowing to remain viable in a liberalized French dairy market without assessing the magnitude of the variations in viability according to strategic choices. Brorsen et al. (1984) have investigated through econometric and simulation techniques the impacts of price variability on Texan wheat producers' marketing margins and viability but they didn't examine a differentiating effect in function of the farm's structural characteristics.

As it reduces investment (Schulte et al., 2018; Wibowo et al., 2023), by focusing on French milk sector, our study contributes to fill the knowledge gap by analyzing the impact of milk price volatility on the level of viability, given the farm's technological use degree which require a subsequent investment. Hence, our aim is to shed a light on the consequences of their structural choices to support their decision making and help them to identify the extent of the adjustments needed to face the increasing milk price volatility. Indeed, technological equipment are becoming more and more available and accessible that it is important to be aware of the impact of its adoption in a potentially volatile dairy market context (Butler et al., 2012; Chatellier et al., 2014).

We use agricultural accounting data from the Farm Accountancy Data Network (FADN) to econometrically estimate the effects of milk price volatility by applying an ordered fixed-effect logistic estimator following Baetschmann et al. (2020). This allows us to account for unobserved and unchanged farm or farmer characteristics that influence the level of farm viability, like the management and learning capacity of farmers.

Using ascending hierarchical classification, our sample of farms is divided into three sub-samples according to the level of use of technological tools. The estimates are made separately for the different sub-samples obtained: low, medium and high level of technology use. Then we compare the magnitude of the milk price volatility between the three groups.

Economic viability is a widely used concept, but no consensus exists about its definitions. While scholars agree with Tichit et al. (2004)'s consideration as 'a good health' of a system which require a given reference called 'reproductive threshold' by Saravia-Matus et al. (2021), there is divergence about its determination.

Some studies contend that good health refers to an ability to provide a decent living or a sufficient remuneration to maintain family labour. Thus, viability is based on the comparison of non-salaried workers income to the opportunity cost of working in the farm which may be represented by the average wage in the agricultural sector or the legal minimum wage (Morel et al., 2017; Barnes et al., 2015; Vrolijk et al., 2010; Phimister et al., 2004). Others extend its definition to the ability to cover the operational and replacement costs of all production input, not only the labour. Thus, they refer to economic indicators such as profitability32 and productivity of the activity to judge whether the farm is viable (Assefa et al., 2017; Wolf, 2012)(Martin et al., 2020; Volkov et al., 2021). But these definitions didn't satisfy Barnes et al. (2020) and Hennessy & Moran (2015) who argue that the viability of the farm should consider its wealth which reflects farmers' well-being and conditions the continuation of activities. However, as this wealth relates to fixed inputs, it rather refers to the long-term viability of the farm (Barnes et al., 2015).

Economic viability differs from financial viability which is limited to the ability to meet financial targets like liquidity, debt ratio and rate of return on equity (Aggelopoulos et al., 2007), by the consideration of economic indicators, such as productivity and opportunity costs, in defining the 'good health' (Spicka et al., 2019). As Savickiene et al. (2016) noted the economic viability of the farm relates to "its capacity to survive, live and develop using its resources" (p.105). This emphasizes the need to account for attributes required for farm functioning such as: value added, intermediate consumption, depreciation, and external factors (Wilczyński & Ko\loszycz (2021). We follow this definition of viability which seems the most comprehensive. Thus, being viable means being able to continue one's activity and even ensure growth despite difficulties and uncertainties. That supposes low vulnerability to risks or disturbances. One can distinguish it from resilience which is associated with the ability to resist, adapt and transform in the face of disturbances (Meuwissen et al., 2019) as it implies being efficient during normal periods. Besides, unlike resilience and sustainability, farm economic viability focuses only on enterprises employing agricultural inputs and is based only on the income they provide, excluding off-farm household income (Spicka et al., 2019).

The direct relationship between economic viability and agricultural product price volatility has rarely been studied in the literature. Brorsen et al. (1984) found a negative relationship between them in the context of the wheat sector in Texas. They considered farms with a rate of return on capital greater than or equal to 4% to be viable. However, they did not consider the strategies adopted by the farms. Furthermore, we assume that this variation in viability may differ according to the level of use of technological equipment.

To manage agricultural price volatility, including milk, farmers rather use generic means like production intensification than instruments such forward contracts and future markets (Assefa et al., 2017; Wolf, 2012).

Technological change, which includes the extended use of technological equipment like automatic milking systems or manure scrapers, is recognized as factors that improve technical efficiency (Ashkenazy et al., 2018; Blayney & Mittelhammer, 1990). But this advantage is not only attributed to equipment which enables the optimization of direct agricultural inputs such as labour, water, organic matter, biodiversity as defined by Shrestha et al. (2021). It may also include other technologies such as genetics. To our knowledge, Hansen et al. (2019), is one of the few studies that specified the role of one equipment. They showed with a stochastic frontier analysis on 212 Norwegian dairy farms that the use of an automatic milking system implies higher income efficiency. This finding conducts us to the following assumption: the degradation of the economic viability of dairy farms is lower for farms using more technological tools than for farms using less technological tools.

Methods

Data source and study population

To test our hypotheses, we use data from the Farm Accountancy Data Network (FADN), between 2002 and 2020. The chosen period is relevant for our study as it corresponds to the beginning of dairy farms exposition to milk price volatility following the 2003 reform of the Common Agricultural Policy. We also collect data on 2002 for our moving average calculations of volatility. We select French dairy farms whose income depend mainly on dairy production and which appear at least five years consecutively in the database. They are located in the national geographic.

Thus, we obtain an unbalanced panel data composed by 1677 unique farms during the observation period. However, we have a significant inequality in the number of farms observed annually. The year 2015 contains the lowest number of observations due to the crisis which hampered the survey.

The data were processed and analyzed using the 15ème version of the STATA software. We deflated all monetary variables to adjust for inflation before our analysis.

Characterization of the economic viability of the studied dairy farms

In our study, we use the indicators of Wilczyński & Ko\loszycz (2021) since it encompasses attributes that characterizes farm economic viability. It relates to the ability to provide enough outcome including subsidies, valued at market prices, to cover the opportunity cost of inputs. We integer subsidies in farms' outcome because our aim consists in explaining their level of viability given the public payment they receive. Moreover, in France, it is mainly composed by direct payments independent to income variation[1].

Thus, outcome result from the total value of output of crops and crop products, livestock and livestock products, of other output, including that of other gainful activities (OGA) of the farms and subsidies. It is the sum of sales and use of (crop and livestock) products and livestock, the change in stocks of products (crop and livestock), the change in valuation of livestock, the various non-exceptional products, minus purchases of livestock. While, the opportunity costs of inputs are measured by intermediary consumption (IC), depreciation (D), wage (W), rent (R), debt interest paid (I), and taxes (T).

Concerning the opportunity cost of self-employed workers, we have opted for the legal minimum wage (LMW) because it expresses the minimum level of remuneration to guarantee a decent standard of living in France. Thus, this value makes it possible to maintain a worker.

$$\text{Viability} = \frac{\text{Outcome}}{\text{IC} + \text{D} + \text{W} + \text{R} + \text{I} + \text{T} + \text{LMW}}$$

The results can be interpreted as follows:

- Viability ≤ 1: the farm is not viable and called "survival" because the provided outcome is inferior to the potential income receive in other employment. It doesn't allow the activity continuation in good conditions.
- 1< Viability ≤ 1.2: farm is "viable" as the generated outcome is enough to ensure the maintenance of the factors of production and to meet the need of the farmers.
- Viability > 1.2: Farm is "in development" thanks to the extra outcome obtained and which can be allocated to the improvement of farms' potential.

During the observation period, the majority of farms are viable. Only 25% of them are not viable, but this percentage vary annually and follow an increasing trend. In contrast, the share of developing farms decreases sharply.

[1] *For more information about the effects of subsidies, especially income risk management, see Trestini et al.(2018) and Vera & Colmenero (2017).*

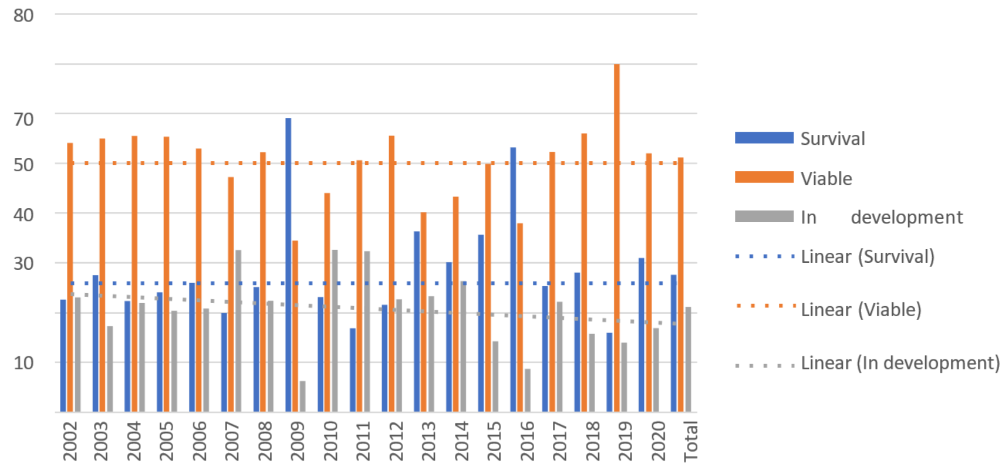

Figure 1: Annual distribution of farms according to their level of viability

Measuring milk price volatility

To calculate the annual volatility of the milk price, we use the method of Santeramo & Lamonaca (2019). Their formula measures how important is the deviation of the current year's price from the trend compared to three-year (y -1, y, y+1) moving average deviation. When it is excessively far from the moving average deviation, the price is considered as volatile in the current year.

We apply this formula to French milk price data from the European price observatory. The use of these aggregated data allows us to avoid the endogeneity problem related to the milk price received by each farm which may depend on a farm's investment ability determined by its viability.

$\sigma_{3y} = \sqrt{\left(\ln\left(\frac{P_y}{P_{y-1}}\right) - \frac{1}{3}\ln\left(\frac{P_{y+1}}{P_{y-1}}\right)\right)^2}$ with P_y represents the milk price in year y

Classifications and characteristics of farm sub-samples

To categorize a farm according to the level of use of technological equipment, we carry, for each year, a k-means classification based on several separating variables. We assume that the characteristics of technological equipped farms vary in time following the development in the society.

Since we use accounting data, we cannot obtain precise values of the existing technological equipment in the farm. Therefore, to identify these characteristics, we rely on the cost associated to the corresponding asset which allows us to have an approximation. The following variables are used:

- Equipment rental value per hectare of utilized agricultural area and per livestock unit (LU)
- Equipment rental costs per hectare of utilized agricultural area and per LU
- Maintenance and repair costs of equipment per hectare of utilized agricultural area and per LU
- Specific facilities value per hectare of utilized agricultural area and per LU
- Machinery and equipment value per hectare of utilized agricultural area and per LU

The **Error! Reference source not found.** shows the average characteristics of the three groups o btained: i) barely, ii) moderately, iii) highly equipped farms. The last group spend the highest fees to maintain and repair materials, being up to €126 per LU, while it amounts to €70 for low technology farms. Besides, the value of materials and tools of moderately (€1,120 per LU) equipped farm equals more than double that of the lowly one (€414 per LU).

Table 1: Characteristics of farms according to their level of use of technological tools

	Low Technology	Intermediate technology	High technology	Total (total average)
Rental of equipment by UAA[38] (€/ha)	0,0928482	0,088836	0,0783891	0,0901802
Equipment hired per LU (€/LIVESTOCK UNIT)	8,326493	10,65464	11,3363	9,410322
Rental charges for materials per UAA (€/ha)	0,0051045	0,0042731	0,0054093	0,0048366
Rental charges for materials per livestock unit (€/livestock unit)	0,4248825	0,4790031	0,7262153	0,4700454
Maintenance and repair of materials per UAA (€/ha)	0,0051045	0,0042731	0,0054093	0,0048366
Maintenance and repair of materials per livestock unit (€/livestock unit)	70,21455	97,40813	126,5615	84,70297
Specialised installations by UAA (€/ha)	1,239739	2,128391	1,130065	1,544821
Specialised facilities by LU (€/LU)	100,6461	228,5518	171,8378	152,0637
Materials and tools by UAA (€/ha)	5,420725	10,67278	16,06533	8,198418
Materials and tools by LU (€/LU)	414,783	1120,73	2291,568	826,6346

Choice of control variables

To build the model of the dairy farm economic viability, we based ourselves on economic studies that focus not only on the economic viability of farms, but also on their income stability and resilience. Indeed, as we have shown in the theoretical framework, these concepts are linked. Income stability is an intrinsic condition for farm economic viability.

It turns out that viability depends on farm structural characteristics and practices, the farmer's-economic attributes and random hazards. Therefore, we include in our model the number of dairy cows (Perrin et al., 2020) and the labour intensity (Spiegel et al., 2021) to indicate the structure of the farm. The number of dairy cows gives us information on the size of the dairy farm and allows us to check its role in the economic viability of dairy farms. Indeed, we expect that a large farm potentially benefits from an economy of scale and resources to ensure the stability of their income (Harkness et al., 2021; Wilczyński & Ko\loszycz, 2021), which contributes to the economic viability of the farm (Vrolijk et al., 2010). Labour intensity, measured by the ratio of the number of paid and unpaid workers and the value of assets, informs us about the importance of workers compared to capital, such as farmland. We expect that a farm with low labour intensity is more viable because as Spiegel et al. (2021) highlighted, it enhances resilience by increasing labour productivity.

Concerning the farmer's attributes, we are mainly interested in their age and agricultural training. Age refers to the level of experience (agricultural or otherwise) that the farmer has and which may have enhanced their managerial capacity. As Dhungana et al. (2004) have shown, agricultural producers become more efficient as they get older. Similarly, education is one of the personal characteristics that can influence management quality, as it provides the skills necessary to promote technical and financial efficiency (Nuthall, 2009). We assume that these determinants of managerial capacity contribute to the economic viability of the farm. However, to avoid multicollinearity with technology use, we exclude it from our control variables.

Two other variables are used to identify the agricultural practices. First, the price quartile to which the farm belongs is used to capture the quality of the milk sold by the farm. Indeed, the price paid to producers is composed of the basic price which is increased according to the quality of the milk (the fat and protein content of milk production or other attributes). The specificity of the milk is a source of an added value that constitutes a resilience factor for farms (Ashkenazy et al., 2018), knowing that it is linked to economic viability (Meuwissen et al., 2019). Secondly, type of farming indicates how diversified it is. Harkness et al. (2021) and Sneessens et al. (2019) have shown respectively that agricultural diversification stabilizes farm income and reduces vulnerability. Thus, it could promote the economic viability of the farm.

Finally, we include in our model of dairy farm viability three types of hazards to which dairy farms are exposed. Economic hazards are captured by the volatility of input and milk prices. We consider the price of concentrates, which is an important cost in dairy production. We use aggregate data from the European observatory to measure its instability. We apply the same formula as for milk price volatility to calculate concentrate price volatility.

Climatic and sanitary hazards are measured by the volatility of milk production. The latter is calculated individually as we use data for each farm from the FADN. Thus, the production volatility results from the difference between the production level of the current year and the average production of the period.

Model specification

Our dependent variable y_{it} corresponds to the viability of dairy farm i in year t. It is a qualitative variable composed of three ordered categories noted c such that i) c=1 represents the worst state called "surviving"; ii) c=2, the fairly good state, which is noted "viable" and iii) c=3, the most favored state, "developing". Therefore, it is modelled following Harkness et al., (2021) and Albert & Chib (1993, P.5) on ordered multinomial variables.

We consider a continuous and latent variable y_{it}^* that indicates the value of the underlying viability of farm i in year t and that allowed it to be assigned into one of the three categories c.

Thus, we model the different states c of y_{it} that are generated by the latent variable z_{it} as follows:

$$y_{it} = c \; si \; y_{it}^* \; \in (\tau_{c-1}, \tau_c]$$

Knowing that $\tau_{ic} = \tau_{jc} = \tau_c$ is constant for any individual i and j, such:

$$y_{it} = \begin{cases} 1 & si & \tau_0 < y_{it}^* < \tau_1 \\ 2 & si & \tau_1 \leq y_{it}^* < \tau_2 \\ 3 & si & \tau_2 \leq y_{it}^* < \tau_3 \end{cases}$$

With $\tau_0 = -\infty < \tau_1 < \tau_2 < \tau_3 = +\infty$

y_{it}^* depends on the following function:

$$y_{it}^* = \alpha_i + X_{it}\beta_1 + VPrix_t\beta_2 + VProd_{it}\beta_3 + VInt_t\beta_4 + R_j + u_{it}$$

Where

- α_i: unobservable characteristics of the holding i such as the management capacity of its operator.
- X_{it} : vector of control variables that indicate the observable characteristics of
- holding i in year t.
- $VPrix_t$: measures the aggregate volatility of the milk price in year t.
- $VProd_t$: measures the volatility of the output of farm i in year t.
- $VInt_t$: measures the aggregate volatility of input prices indicated by the price of concentrates in year t.
- β_k : the parameters to be estimated for the variables of interest and the control variables
- u_{it}: time-varying unobservable term

Estimation method

To estimate the parameters of our model, we apply a fixed effect. Indeed, as the random effect assumes a normal distribution and independence from the explanatory variables of the term representing the unobservable and time-invariant characteristics of individuals (Greene, 2012), we prefer to apply the fixed effect which relaxes this strong restriction. Since the fixed effect is only valid with the logistic distribution function (Muris, 2017), the probability of observing modality c is obtained as follows:

$$\Pr(y_{it} = c|X'_{it}, \alpha_i) = P(\tau_{c-1} < \alpha_i + X'_{it}\beta + u_{it} < \tau_c|X'_{it}, \alpha_i)$$
$$= \Lambda(\tau_c - X'_{it}\beta - \alpha_i) - \Lambda(\tau_{c-1} - X'_{it}\beta - \alpha_i)$$

With

$\Lambda(\mathrm{x}) = e^x/(1 + e^x)$ represents the cumulative distribution function of the distribution law logistics.

The probability depends on X'_{it}which is the vector of all explanatory variables and β which is the vector of all parameters.

To estimate the parameter vector β, the maximum likelihood estimator must be used. The likelihood function is expressed as follows:

$$L = \prod_{i=1}^{N}\prod_{t=1}^{T}\prod_{c=1}^{k}(P_{it})^{y_{it}=c}$$

$$L_n(\beta,\tau,\alpha)=\prod_{i=1}^{N}\prod_{t=1}^{T}\prod_{c=1}^{k}[\Lambda(\tau_c-X'_{it}\beta-\alpha_i)-\Lambda(\tau_{c-1}-X'_{it}\beta-\alpha_i)]^{1\{y_{it}=c\}}$$

Then, this function must be expressed in logarithm as follows:

$$Log\ L=\sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{c=1}^{k}(P_{it})^{y_{it}=c}$$

Finally, the following non-linear system of equations must be solved:

$$\frac{\partial Log\ L}{\partial\beta}=0$$

As our dependent variable is an ordered categorical variable, we estimate the parameter using feologit of Baetschmann (2012), Baetschmann et al. (2015) et Muris (2017). This estimation method presents a lot of advantage as it allows to solve the parameter incidence by using sufficient statistic[1]. The dependent variable is transformed into a binary variable for which the maximum likelihood estimator conditional on this statistic works. Then it recombines them to obtain the parameters of the explanatory variables of our initial dependent variable. Let us note d_{it}^{c} the new binary dependent variable. It is given by:

$$d_{it}^{c}=1(y_{it}\geq c)$$
$$d_{it}^{c}=0(y_{it}<c)$$

Let $\bar{d}_i^c$ be the number of times $d_{it}^{c}=1$ is observed for holding i during the observation period.

$$\bar{d}_i^c=\sum_{t=1}^{T}d_{it}^{c}$$

The latter is the sufficient statistic on which the maximum conditional likelihood and approximates α_i.

Thus, the probability of observing our new binary dependent variable d_i^c is equivalent to $(d_{i1}^c,\dots,d_{iT}^c)'$ conditional on the value of $\bar{d}_i^c$. It is obtained by:

$$P_i^c(\beta)\equiv\Pr\left(d_i^c\middle|\sum_{t=1}^{T}d_{it}^c=\bar{d}_i^c\right)=\frac{\exp\{d_i^{c\prime}(X_i\beta-\tau_i^*)\}}{\sum_{j\in B_i}\exp\{j'(X_i\beta-\tau_i^*)}$$

With

$j=(j_1,\dots,j_T)$ tel que j_t={0,1} et $\sum_{t=1}^{T}j_t=\bar{d}_i^c$

B_i represents the set of possible vectors j.

After the log transformation, the conditional likelihood function becomes:

$$LL^c(\beta)=\sum_{i=1}^{N}\log P_i^c(\beta)$$

[1] *A statistic is sufficient when "no other statistic that could be estimated from the sample provides additional information to identify the value of the parameter to be estimated" (Fisher, 1922, p. 310).*

It no longer depends on time-invariant individual unobservable characteristics α_i. After combining the information, the BUC (Blow-up and cluster) estimator is:

$$LL^{BUc}(\beta) = \sum_{c=2}^{k} LL^{c}(\beta)$$

Results

The estimation of models per subsample defined according to the level of use of technological tools was validated by the likelihood ratio test. Indeed, the separation of the samples brings more explanation to our model than integrating the variables of interest in interaction with the other variables. The integration of other control variables such as legal status does not bring us any additional information. Table 2 shows the results of our basic model. It shows that all coefficients are jointly and significantly different from zero according to the Wald test. The coefficients estimated by our main model represent the marginal effects of the explanatory variables on the latent variable of sustainability. However, as we are most interested in the viability categories and in identifying the effect of milk price volatility on category membership, we calculate the marginal effect on average. This parameter tells us the variation in probability to belong on one category following a unit variation in the explanator variable. The direction of the relationship is indicated by the sign of the corresponding coefficient.

Effects of milk price volatility on economic viability differentiated by level of use of technological tools on dairy farms

The results in table 2 below show us that the parameters of milk price volatility estimated using ordered fixed-effect logistic regressions are significantly negative at the 5% confidence level for all three subsamples. Thus, if milk price volatility increases by one unit, ceteris paribus, the probability of surviving increase. However, the magnitudes of the variation differ significantly in function of the level of use of technological equipment. Indeed, the viability of farms with low use of technological tools shows a higher sensitivity (-13.20) to a unit increase of milk price volatility compared to the viability of those with a higher level of use (-11.06). This sensitivity appears to be lowest for farms with a medium level of technology (-4.164). In other words, the use of technological tools reduces the impact of volatility on farm economic viability, but there is a limit of risk reducing equipment.

This result confirms the concerns and roles played by technological tools and the advantages drawn from capital use. The increase in productivity should help to mitigate the consequence of milk price volatility. Agricultural technologies allow farmers to avoid certain tasks that can be automated and potentially free up time for the farmer to focus on farm or milk price volatility management. Besides, it is possible to allocate time for information retrieval, and to react more quickly in an appropriate way. However, as these tools also represent additional costs such as maintenance costs[1], they can increase the farm's operating costs and reduce its financial capacity.

[1] *The Table 1 (in the section "Classifications and characteristics of farm sub-samples") describing the characteristics of the three groups clearly shows the superiority of the median cost of equipment maintenance the high-tech group compared to the low- and medium-tech groups.*

Table 2: Ordered logistic fixed effect of short-term viability of sub-samples by level of technology use

	(1) Lowly technologized holding	(2) Moderately technologized holding	(3) Highly technologized holding
Milk price volatility	-13,20***	-4,164**	-11,06***
	(2,135)	(1,735)	(2,310)
Volatility of milk production	1,075	-0,336	-1,866
	(0,758)	(0,958)	(1,553)
Price volatility of concentrates	10,03***	2,177	2,650
	(2,475)	(1,567)	(2,600)
MILK PRICE QUARTILE			
Q1	Référence	Référence	Référence
Q2	0,680***	0,623***	0,303
	(0,184)	(0,236)	(0,269)
Q3	0,998***	0,838***	0,338
	(0,190)	(0,270)	(0,308)
Q4	1,162***	1,546***	0,669*
	(0,239)	(0,328)	(0,361)
Type of farming			
Specialized dairy cattle	Référence	Référence	Référence
Mixed beef and dairy cattle	0,186	0,652	0,223
	(0,391)	(0,558)	(0,559)
Poly-breeding	0,703	1,036	0,620
	(0,640)	(0,653)	(0,760)
Mixed crop livestock	0,924	0,412	0,999**
	(0,602)	(0,374)	(0,466)
Intensification level			
Extensive	Référence	Référence	Référence
Semi-intensive	-0,132	0,0351	0,124
	(0,219)	(0,224)	(0,274)
Intensive	-0,353	-0,570	-0,0458
	(0,327)	(0,361)	(0,392)
Labour intensity	0,000431***	0,000269*	0,000318*
	(0,000162)	(0,000154)	(0,000177)
Age of the farm holder	0,0498*	-0,00646	0,0243
	(0,0256)	(0,0183)	(0,0157)
Cow milk herd size	0,0279**	-0,00132	0,0602***
	(0,0124)	(0,0103)	(0,0150)
Observations	1 800	1 280	947

Robust standard deviation in parenthesis; ***, ** et * indicate statistical significance at 1%, 5% et 10%.

To better understand our results, we focus on the variation in the probability of belonging to each viability degree following a unit variation in milk price volatility. These are presented in table 3.

In the case of the two groups, there are significant increases in the probability to be survival or non-viable for all the three groups (low, medium, and high use of technological equipment) when volatility increases, all other things being equal. Farms with a low level of use of technological tools are the most affected, followed by those with a high level of use. Indeed, their probabilities of being non-viable rise respectively by 2.47% and 2.12%. In contrast, the probabilities of becoming non-viable increase by 0.83% for farm using moderately technology.

Concerning the probability of becoming viable, it increases for the low-tech group, although this change is very small, but decreases for the medium and high-tech groups. Despite this positive change in the probability of being viable, the situation seems to be more worrying for the low-tech farms when the milk price fluctuates more. The benefits of technological tools outweigh their limitations, especially in the face of milk price volatility.

Table 3: Average marginal effects of milk price volatility by level of use of technological tools

	Probabilities change
Lowly technologized holding	
1. Surviving	2,470
2. Viable	0,0783
3. In development	-2,548
Moderately technologized holding	
1. Surviving	0,828
2. Viable	-0,102
3. In development	-0,726
Highly technologized holding	
1. Surviving	2,121
2. Viable	-0,233
3. In development	-1,888

The offsetting effects between variables, presented in table 4 tell us about the adjustments needed on labour intensity and on the number of dairy cows to counterbalance the changes in viability level. Low, medium and high technology farms increase respectively the value of assets per worker by €298, €154.8 and €347.8 to compensate for the decrease in viability due to a unit increase in milk price volatility. In other words, they resort to an increase in the number of dairy cows of 4.73 and 1.84 respectively for the low and high technology farms.

Table 4. Offsetting effects of milk price volatility with: i) cow milk number and ii) labour intensity

	Lowly technologized holding	Moderately technologized holding	Highly technologized holding
Cow milk herd size	4,71**	-	1,84***
Labour intensity (Assets value per worker)	-306,26 ***	-154,8*	-347,8*

***, ** and * indicate statistical significance at 1%, 5% et 10%.

Effects of control variables on the economic viability of dairy farms

Some of the control variables' estimated parameters are also significant at least 90% and even 99% confidence levels. First of all, for low technological farms, the concentrate price volatility coefficients is significantly positive, in opposite to our expectation (negative effect on viability).

We assume that the high dependence of low-tech farms on equipment rental and the low ownership of equipment or facilities makes them flexible to manage concentrate purchases in a countercyclical way to deal with input price volatility. Thus, for example, they can take advantage of a price drop to build up their stock and benefit from this stock when prices rise.

For the other control variables, their correlation with sustainability is rather consistent with our hypotheses. Indeed, the variable indicating the presence of a high payment for the production of high value-added milk (the quartile of the price to which the farm belongs) and the age of the farmer are significantly and positively correlated with the economic viability of the farms. The viability of the group of farms belonging to the upper quartile is higher than that of the group of farms included in the lower quartile. Thus, our result coincides with the prediction of Vrolijk et al (2010) that economic viability depends on the price level in addition to its variability. Furthermore, dairy farms tend to be more viable when their operators are older, especially for low technological use farms. This relationship reflects the importance of experience in determining the viability of dairy farms. We hypothesize that the professional experiences gained by farmers not only in dairy or agricultural production, but also outside the agricultural sector contribute to the multiplication of skills needed to achieve better economic results, without too much technology.

Concerning the results obtained for the type of farming, a significant difference in viability is observed between farms specialized in dairy cattle and diversified farms, mixing crop and livestock, notably for highly equipped farms. In other words, making the available farmland profitable with other productions leading to independent markets or risks or to complementary land uses, favours more flexibility to adapt to the different hazards and would allow to better insure economic viability.

Robustness and limitations of the results

To test the robustness of our results, we made four main modifications.

- *i) Changing the measure of milk price volatility:* we calculate the volatility of the milk price paid to individual farms instead of the aggregate milk price. It is obtained by the deviation of the price from its average value during the whole observation period. We cannot calculate the coefficient of variation based on a three-year moving average because the FADN database is a non-cylindrical panel.
- *ii) Extension of the sample studied:* we select farm appearing three years consecutively in the database instead of five years.
- *iii) Use of other measures of diversification:* following Harkness et al. (2021), we considered two other measures of diversification. We integrate them in the model in a sequential way, to avoid a problem of multicollinearity. a) First, the agricultural diversification which consists in evaluating the diversity of the existing animal and vegetable productions within the farm. This is obtained using the Herfindhal index below. This index is based on the proportion of gross product (p_i) generated by the different types of agricultural activities[41] i. Its value, between 0 and 1, increases (decreases) as the level of specialisation of the farm is high (low). b) Next, we introduce farm diversification which measures the diversity and importance of the farm's non-farm activities such as on-farm processing. The diversification of the holding is calculated by the ratio of the share of products from agricultural production to the total products of the year.

$$Indice\ de\ Herfindahl = \sum_{i=1}^{n} (p_i)^2$$

i) *Non-annual classification of farms according to the level of technological tools use:* We test the effect of an ascending hierarchical classification applied simultaneously on all the observations of the period considered in our study.

The parameters of milk price volatility in our regressions remain significantly negative except for the volatility of the individual milk price. Indeed, the use of an absolute average may lead to an overestimation of volatility and would reduce its correlation with economic viability despite its strong correlation with the relative measure of volatility (coefficient of variation calculated from the three-year moving average of the aggregate milk price).

In addition, the values of the coefficient do not always remain close to the basic model's one. However, the order of magnitude is still almost maintained throughout the sub-samples' regressions. Indeed, the parameters gravitate around the bounds of the confidence interval of those of the basic model, with the exception of the parameters estimated when applying the absolute classification. Consequently, we deduce that our results are relatively robust. However, they are limited in the context of a relative classification of the level of use of technological tools, which we consider to be the most relevant. Indeed, given the structural change that has taken place in the dairy sector, we aim to highlight the sensitivity of farms considered as high-tech according to the criteria of the time.

Table 5. Robustness tests of milk price volatility parameters according to the level of use of technological tools

		(i)	(ii)	(iii) (a)	(iii) (b)	(iv)
	Basic model	Individual milk price volatility	Larger samples (> 3 years) appearance)	Agricultural diversification	Diversification of operation	Overall farm classification
Low-tech holding						
Coefficients	-13.20***	-2.196	-13.77***	-14.72***	-13.31***	-6.649***
Standard deviations	(2.135)	(1.511)	(2.196)	(2.071)	(2.114)	(1.029)
Medium-tech holding						
Coefficients	-4.164**	-1.534	-4.020**	-4.693**	-3.856**	-10.08***
Standard deviations	(1.735)	(1.301)	(1.754)	(1.835)	(1.714)	(1.830)
High-tech holding						
Coefficients	-11.06***	-1.054	-11.92***	-14.68***	-10.33***	-5.313
Standard deviations	(2.310)	(1.832)	(2.318)	(2.593)	(2.303)	(4.250)

*p<0.10, **p<0.05, ***p<0.01

Conclusion

Our work has quantified the impacts of technology use levels on the variation of economic viability of dairy farms when milk price volatility changes. Our results show that the degradation of economic viability is significantly lower for farms with moderate or high use of technological tools compared to those with low levels of use. Thus, the level of technology use is an important heterogeneity factor in determining the evolution of farm viability in a volatile market. Finding the right level of equipment is therefore necessary to reap the benefits it offers without being burdened by the associated costs. Therefore, it is important not to reduce investment in technological tools too much in response to increased volatility in the price of milk to avoid undermining the economic viability of the farm.

The generalization of our results should be carried out with caution because they are sensitive to the methods of calculating the volatility of the milk price and the classification of farms according to their level of technological tools use. Indeed, they indicate the consequences of an increased volatility of the average milk price at national level, without considering territorial specificities. In addition, farms should refer to annual references to situate their level of technological use before referring to our results. Furthermore, our results could be deepened by analyzing the severity of the lack of viability of farms with low technological use following an increase in milk price volatility.

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