Quantile Regression: Applications in Agri-Business Management

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Introduction

Agriculture is often described through averages-average yield, average price, average income. But what if these averages are hiding more than they reveal? Consider two farmers using the same quantity of fertilizer on similar land. One achieves high productivity and profits, while the other struggles to break even. If we rely only on averages, both farmers appear to be performing "normally." In reality, their experiences are vastly different.

This limitation is not just theoretical, it has important implications for real-world decision-making in agribusiness. Farmers, policymakers, and businesses frequently base their strategies on average outcomes, assuming that all participants respond similarly to changes in inputs, prices, or policies. However, agriculture is inherently heterogeneous, with variations in land quality, access to technology, market integration, and risk exposure leading to diverse outcomes across producers and firms (Birthal *et al.*, 2015; FAO, 2017).

Traditional statistical tools, particularly Ordinary Least Squares (OLS) regression, reinforce this "average thinking" by focusing on the mean relationship between variables. While useful, this approach can mask important differences across the distribution of outcomes, especially in the presence of skewed data, heteroscedasticity, or outliers (Wooldridge, 2010). As a result, policies or business strategies derived from mean-based analysis may fail to address the needs of both low-performing and high-performing segments effectively.

To overcome these limitations, a more nuanced analytical framework is required. Quantile regression, introduced by Koenker and Bassett (1978), provides such an approach by examining how relationships between variables vary across different points of the outcome distribution. Instead of focusing solely on the average effect, it enables researchers to analyze the impact of explanatory factors on lower, median, and upper segments of the population.

By moving beyond averages, quantile regression offers deeper insights into agricultural systems, helping stakeholders design more targeted interventions, improve efficiency, and promote inclusive growth. This article explores how this powerful yet underutilized tool is reshaping decision-making in agribusiness management.

The Problem with Averages in Agriculture

Averages offer a convenient summary, but they often mask the diversity within agricultural systems. An increase in average yield or income does not necessarily mean that all farmers are better off, gains may be concentrated among a few high performers, while many continue to lag behind (FAO, 2017).

Similarly, average prices can be misleading, as farmers experience different market conditions depending on timing, access, and scale. Smallholders, in particular, often receive lower-than-average prices due to limited bargaining power (Birthal *et al.*, 2015). These limitations arise because traditional approaches focus only on average effects, assuming uniform responses across all farmers. In reality, agriculture is highly heterogeneous, and outcomes vary widely across different groups (Wooldridge, 2010).

Types of Regression Approaches and Their Relevance in Agribusiness

Different regression techniques are used in agribusiness research to analyze relationships between variables, each offering unique insights depending on the nature of the data and research objective. The following table summarizes key regression models, their basic equations, and their practical relevance in agricultural and market analysis.

What is Quantile Regression? A Simple Perspective

If averages do not tell the full story, the next question is: how do we capture the differences within agriculture? Quantile regression provides a simple yet powerful answer. Traditional regression methods, such as Ordinary Least Squares (OLS), focus on estimating the average relationship between variables. This approach explains how an independent variable affects the dependent variable on average. However, agriculture rarely behaves in averages.

Quantile regression extends this framework by estimating relationships at different points of the distribution:

$$Q_\tau (Y|X) = \beta_0(\tau) + \beta_1(\tau) X$$

where τ represents different quantiles such as lower (0.25), median (0.50), and upper (0.75) levels (Koenker & Bassett, 1978).

Quantile regression extends this idea by estimating relationships at different points (quantiles) of the outcome distribution (Koenker & Bassett, 1978; Huang *et al.*, 2017). The concept using the "check function" (Fig. 1) which forms the basis of quantile regression estimation. Unlike traditional methods that minimize squared errors, quantile regression assigns asymmetric weights to positive and negative residuals depending on the chosen quantile. This enables the model to estimate different relationships for lower, median, and upper segments of the data (Huang *et al.*, 2017).

Table 1: Overview of regression techniques and their applications in agribusiness

Type of Regression	Basic Equation	Practical Insight in Agribusiness
Linear Regression (OLS)	$Y= \beta_0 + \beta_1X_1 + \beta_2X_2 +...+ \beta_nX_n + \varepsilon$	Estimates average relationships (e.g., yield vs inputs), but assumes uniform response across farmers.
Logistic Regression	$\log(p/1-p) = \beta_0 + \beta_1X_1 + \beta_2X_2 +...+ \beta_nX_n$	Used for binary outcomes (e.g., technology adoption), focusing on probability rather than magnitude.
Polynomial Regression	$Y=\beta_0 + \beta_1X + \beta_2X_2 + \beta_3X_3 +...+ \beta_nX_n + \varepsilon$	Captures nonlinear patterns such as crop growth or price trends.
Ridge Regression	$\sum(Y-\beta_0-\sum\beta_iX_i)^2 + \lambda\sum\beta i^2$	Handles multicollinearity in datasets with highly correlated variables.
Lasso Regression	$\sum(Y-\beta 0-\sum\beta_iX_i)^2 + \lambda\sum|\beta_i|$	Identifies key factors (e.g., price, quality, GI label) influencing consumer demand by removing irrelevant variables.
Probit Regression	$P(Y=1/X) = \Phi (\beta_0 + \beta_1X_1 +...+ \beta_nX_n)$	Estimates the probability of decisions such as technology adoption or premium product choice.
Non-linear Regression	$Y= ae^{bX} + \varepsilon$	Models complex biological and economic relationships beyond linear trends.
Poisson Regression	$\text{Log} (\lambda)= \beta_0 + \beta_1X_1 +...+ \beta_nX_n$	Used for count data (e.g., disease incidence, purchase frequency).
Elastic Net Regression	$\sum(Y-\beta_0-\sum\beta_iX_i)^2 + \lambda1\sum|\beta_i| + \lambda2\sum\beta_i^2$	Handles correlated inputs (e.g., fertilizer, labour, irrigation) to improve yield and profitability predictions.
Quantile Regression	$Q_\tau(Y/X) = \beta_0 + \beta_1X_1 +...+ \beta_nX_n$	Shows how impacts differ across segments (e.g., price-sensitive vs premium consumers).

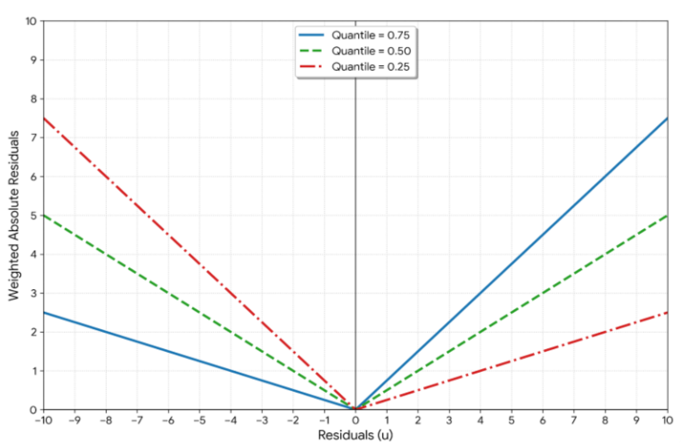

Fig. 1: Distribution patterns of quantiles

To understand this, consider the effect of fertilizer on crop yield. An average-based model might suggest a moderate positive impact. But in reality, farmers with better irrigation and technology may experience much higher gains, while resource-poor farmers may see only marginal improvements. Quantile regression captures these differences by estimating separate effects across performance levels.

The same logic applies to agricultural markets. While average analysis may show that price influences demand, quantile regression can reveal that price-sensitive consumers behave very differently from premium buyers who value quality, branding, or certification (Bekkerman *et al.*, 2013).

Why Quantile Regression Matters in Agri-Business

Quantile regression has wide-ranging applications in agribusiness as it captures variations across different segments rather than relying on average outcomes. This makes it particularly useful in addressing the inherent heterogeneity in agricultural systems.

1. ***Farm Productivity and Input Use Efficiency:*** Agricultural output depends on inputs such as fertilizer, irrigation, labour, and technology, but their effectiveness varies across farmers. Quantile regression reveals that inputs may have limited impact among low-yield farmers due to constraints like poor soil quality or lack of irrigation, while the same inputs generate significantly higher returns for top-performing farmers. This highlights the need for targeted interventions rather than uniform recommendations.
2. ***Consumer Behaviour and Willingness to Pay:*** In differentiated markets such as organic and Geographical Indication (GI) products, consumer preferences are not uniform. Quantile regression identifies distinct segments, price-sensitive consumers at lower levels and premium buyers at higher levels who value quality, certification, and branding. This is particularly relevant for GI rice markets, where awareness and perceived authenticity influence willingness to pay, supporting better market segmentation and pricing strategies.
3. ***Agricultural Price Dynamics and Market Risk:*** Agricultural prices are highly volatile and influenced by supply conditions, weather shocks, and policy changes. Average price analysis often masks extreme variations. Quantile regression shows that during surplus periods, prices are driven by excess supply and weak demand, whereas during scarcity, factors like climate variability and input costs dominate. These insights are crucial for designing effective price stabilization and risk management strategies.
4. ***Wage Inequality and Labour Dynamics:*** The agricultural labour market exhibits significant wage disparities. Quantile regression demonstrates that factors such as education and experience have minimal impact at lower wage levels but significantly increase earnings at higher levels, thereby widening inequality. This understanding is essential for designing inclusive labour policies and skill development programs.
5. ***Agribusiness Performance and Investment Decisions:*** Firms differ in efficiency, scale, and profitability, making average-based analysis inadequate. Quantile regression reveals that investments in technology, infrastructure, and market integration yield limited benefits for low-performing firms but generate substantially higher returns for efficient enterprises. This helps in better resource allocation and strategic decision-making.
6. ***Supply Chain Efficiency and Market Linkages:*** Improvements in supply chains do not benefit all participants equally. Quantile regression shows that smallholders often gain less from better logistics and market access due to constraints, while larger producers benefit more. This highlights the need to strengthen market linkages and infrastructure for marginal farmers.
7. ***Policy Evaluation and Targeted Interventions:*** Agricultural policies often assume uniform impact across beneficiaries. Quantile regression enables policymakers to assess how different groups respond to interventions such as subsidies or support prices. By identifying these differences, policies can be redesigned to ensure greater inclusivity and effectiveness.

Conclusion

Agriculture is too complex and diverse to be understood through averages alone. While traditional approaches provide a simplified view, they often overlook the variations that define real-world outcomes. Farmers differ in their access to resources, consumers vary in their preferences, and agribusiness firms operate under unequal conditions. Ignoring this diversity can lead to incomplete analysis and less effective decisions. Quantile regression offers a more nuanced perspective by revealing how relationships change across different levels of performance. It shifts the focus from a single "average effect" to a broader understanding of variability, helping identify what works for low-performing groups, what drives success among high performers, and where targeted interventions are most needed (Koenker & Bassett, 1978). For policymakers, this means designing more inclusive and efficient agricultural policies. For businesses, it enables better market segmentation and strategic planning. For researchers, it provides a robust framework to capture the true complexity of agribusiness systems. In a sector where variability is the norm, moving beyond averages is not just an analytical improvement; it is a necessity. Quantile regression, therefore, is not merely a statistical tool, but a practical approach for achieving more informed, equitable, and effective outcomes in agribusiness.

References

Bekkerman A., Brester G. W. and McDonald T. J. (2013). A semiparametric approach to analyzing differentiated agricultural products. *Journal of Agricultural and Applied Economics*, 45(1), 79–94.

Birthal P. S., Chand R., Joshi P. K., Saxena R. and Rajkhowa P. (2015). Formal versus informal: Efficiency, inclusiveness and financing of dairy value chains in Indian Punjab. *Journal of Rural Studies*, 38, 52–63.

Food and Agriculture Organization (FAO) (2017). *The Future of Food and Agriculture – Trends and Challenges*. Rome: FAO. https://www.fao.org/agrifood-economics/publications/detail/en/c/471795

Huang Q., Zhang H., Chen J. and He M. (2017). Quantile regression models and their applications: A review. *Journal of Biometrics & Biostatistics*, 8(3), 354–360.

Koenker R. (2005). *Quantile Regression*. Cambridge: Cambridge University Press.

Koenker R. and Bassett G. (1978). Regression quantiles. *Econometrica*, 46(1), 33–50.

Wooldridge J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). Cambridge, MA: MIT Press.

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