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Distributional and Tail-Dependent Perspectives in Economic Relationships: A Review of Quantile Regression Application

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ABSTRACT

There is an increased proportion of studies using quantile-based regression methodology (QR) in economics. They offer a robust alternative to classical mean regressions, which can estimate non-normal variables with distributional heterogeneity in the dependent variable. This study synthesizes the theoretical foundations, methodological advancements, and empirical application of QR in economics that traces the evolution from the foundational work of Koenker and Basset. The targeted studies are from Scopus. Bibliometrix library in R is used for bibliometric analysis, and Structured Literature Revie (SLR) is conducted on selected studies. The Scopus query started with 250 studies and was finalized at 53 studies that focused on the motivation of using QR, comparison of ordinary least squares (OLS), and QR in economics. The systematic review has spanned the past decade. The consolidation of fragmented evidence showed that QR can advance econometric debates by providing superior data insights. The insights presented in this review are aimed at bridging the gap between econometric development and applied economic policy research. This paper contributes to a deeper understanding of distribution-sensitive modeling strategies, offering valuable implications for economists in academia, government, and industry.

1 | Introduction

Human economic behavior is complex in design, which makes it difficult to conform to the simplifying assumptions of classical linear regression models (CLRM), particularly that their behaviors are assumed to be normal in nature, and the relationships depict a constant and linear pattern across the distribution of the dependent variable. For example, in income-consumption relationships, the marginal propensity is likely to change when an income cluster of households changes, creating heterogenous behavioral patterns with ordinary least squares (OLS), which may, in turn, oversimplify using conditional mean as a point estimate of the relationship (Koenker and Bassett 1978). This behavior is denoted as distributional heterogeneity, which can be observed in other economic relationships like monetary policy transmission, inflation dynamics, and economic growth, whereby the point estimate may also depend on the economic state and time period.

The methodological limitations of OLS include the presumption that the slopes are constant for any distributional position of the dependent variable, which led economists to explore complex models. While OLS was the best linear unbiased estimator (BLUE) under Gauss–Markov's assumptions, the use of the mean as a point estimate makes the model over restrictive and ignores the information at the tails and within subclusters of data (Buchinsky 1998). Non-normality of residuals coming from skewed or extreme value data may lead to issues for inference, especially when the data may have subdistributional groups. Traditionally, data transformations, interaction terms, and polynomial specifications are tested to absorb this distributional heterogeneity, but these approaches can only capture the distributional heterogeneity from the independent variable side and may not fully comprehend the complexity of the relationship, which is distributional position–dependent.

Quantile regression (QR) was introduced by Koenker and Bassett (1978) as an alternative approach that provides conditional quantile functions. This methodology can examine how explanatory variables are affected differently at different points in the distribution of outcome variables, revealing heterogenous treatment effects which were hidden in OLS-based models. QR had thus emerged as an alternative statistical tool for an in-depth complete assessment of stochastic relationships. This model is also flexible, in cases, where the data are normally distributed, QR estimates equate to OLS estimates. There were several phases in the evolution of QR models. It started in the 1980s for cross-sectional contexts, then extended into time-series and panel data. The recent variants include quantile autoregressive distributive lagged (ARDL) models, quantile vector autoregressive (VAR) systems, and quantile on quantile (QonQ) models. Recent development also introduced quantile estimation within the generalized method of moments (GMM) to address endogeneity.

Contemporary economic analysis involves confronting datasets that are heavy on tails, distributional asymmetries, and heterogenous subgroups, especially in the case of microdata with repeated annual surveys like Multi-Indicator Cluster Surveys (MICS), World Values Surveys (WVS), Global Entrepreneurship Monitor Surveys (GEM), and so forth. In such cases, QR is a useful approach by providing flexibility, robustness, and insights into conditional relationships. The flexibility can be understood in the scenario of policy intervention for income inequality, where changes in income distribution/cluster may have differential effects. In economics, there can be scenarios where the generic behavior of the dependent variable is expected to change (like the tax-backets effect and cases that use piecewise regression where the breaks could be multiple or unknown) with the size of the dependent variable. While all the functional form transformations can be adapted in QR models, it can further extend the model in terms of the transformation of the dependent variable, where OLS is silent. In such cases, QR can perform better than OLS. Other examples include the case of financial contagions, a tail-dependent that requires robust risk assessment.

The development of QR models is not free of computational and performance challenges. Computational complexity is substantially increased when implementing QR models in panel data or time series data, when compared to cross-sectional data. The inclusion of dynamic effects in the presence of fixed effects induces biasness. The interpretation of the QR model must also be carefully handled, especially when the data are skewed and when the quantile slopes are connected to their economic meanings across quantiles. This step may only represent a selection of effects rather than handling distribution heterogeneity. Lastly, there is a debate about how to decide the number of quantiles to be estimated. The use of statistical and economic reasons has its own trade-offs in handling distributional analysis versus parsimony in interpretation and implementation.

Practically, a QR model in policy analysis raises additional consideration regarding connecting quantile effects with actionable policy recommendations. While QR points towards heterogenous policy, it does not help how policy makers can retrofit this into their intervention design. Recent studies also integrated machine learning models with QR, which improved the performance of these robust models (Arshed, Bakkar, et al. 2025). However, this setup has its own interpretability challenges. Still, there are a growing number of studies that recognize QR as a complementary model rather than a replacement for OLS. Research objectives, data characteristics, and theoretical flexibility are primary supports that motivate the selection of OLS or QR.

This study reviews the evolution, application, and methodological development of QR in economics. By adapting a critical perspective in acknowledging the contribution and limitations of QR, this study presents the comparative advantage of QR and OLS. We conduct systematic reviews on empirical applications of QR to enhance understanding within economic research. The study starts with a genealogical approach that discusses the methodological evolution of Koenker and Bassett's (1978) original formulation. A further examination includes how the economic research community has adapted or modified QR models. This study synthesized the broader trends in econometrics that gained from the flexibility and robust nature of QR that can handle theoretical rigor and data complexity. The outcomes are categorized in terms of how the QR methods contribute to the literature.

While we discuss the growing reputation of QR in terms of flexibility in data handling and inference beyond the estimation of slopes, this model is still considered underdeveloped in economics. This study used the concept development frameworks of Howie and Bagnall (2020) and Podsakoff et al. (2016) to synthesize the QR model as a distribution-sensitive econometric assessment and presents its methodological evolution, empirical scope, and future development. Thus, this study moves beyond a descriptive inventory to a theory-oriented synthesis of quantile-based econometrics.

The objective of this review is to systematically synthesize theoretical developments, empirical applications, and methodological innovations using QR in economics. The specific questions set by the study are as follows:

RQ1: What are the main motivations for employing QR in economic research?
RQ2: Which methodological variants of QR have been developed and applied?
RQ3: In which domains of economics has QR been applied, and what insights emerge compared to OLS?
RQ4: What challenges and gaps remain, and what directions for future research are suggested?

This study conducts the SLR using guidelines provided by studies like Okoli (2015), Sauer and Seuring (2023), and Tingelhoff et al. (2025). The Scopus database is used to find relevant studies. Using a specified search query, this study extracted 47 studies between 2011 and 2025. The next section details some prominent recommendations extracted from the SLR. This review positioned QR not only as a methodological contribution but also as a theoretical bridge that can broaden the econometric modeling frameworks with dynamic capabilities and increased stakeholder involvement by subcluster policy evaluation.

2 | Background

2.1 | Methodological Evolution of Quantile Regression

The methodological evolution of QR started from the work of Koenker and Bassett (1978), who introduced the QR by expanding the OLS regression that can estimate conditional quantile functions rather than conditional means. This model minimizes asymmetrically weighted absolute deviations and, for the case of medians, it uses the least absolute deviations. Authors demonstrated that the outcomes can be generated using a linear programming technique, making it feasible to estimate. Bassett and Koenker (1982) later improved the computational algorithm and added regression rank tests in the post-regression inferences. During this time, the algorithm was refined and available for extensive analysis (Koenker and D'Orey 1987). The asymptotic theory of QR was further refined by Gutenbrunner and Jureckova (1992), who included the Bahadur representation for QR estimators (Kiefer 1967) linking the model with theoretical foundations that enabled model-sophisticated inferences in QR. Koenker and Machado (1999) developed the goodness-of-fit statistic for this model, which enabled the model evaluation and comparison with OLS, as the traditional R square was not sufficient in this case (Uribe and Guillen 2020). Furthermore, significant development in the methodology was proposed by Chernozhukov and Hansen (2005, 2008, 2006), who enabled the model to use instrumental variables within QR; thus, this model became able to address the endogeneity concern in the causal inference in economic cross-sectional data. Machado and Mata (2005) developed counterfactual decomposition methods for QR to observe distributional changes in covariances compared to changes in conditional distributions. The more recent advances improved the computational efficiency and scalability of the model, like the inclusion of penalized QR for high-dimensional data. Bayesian approaches and machine learning integration provided a nonparametric QR model compared to OLS, which added value in contemporary economic research (Karlsson 2007).

2.2 | Empirical Applications for Quantile Regression

There is a growing recognition of QR as an important analytical tool that can address diversity in the data. Empirical studies have adopted this model with an aim to provide another methodological perspective, which was overlooked by OLS-based models. In this section, we overview some perspectives, which will be used to give an important background of this study while also being used to develop the search query for the SLR analysis.

QR model utilization has been observed in macroeconomic policy analysis studies where the distributional effects may point towards dedicated policy design. Dao and Nguyen (2025) used Bayesian QR in macroeconomic stress testing. According to them, this model can help in assessing tail risks and extreme economic scenarios, which are important for financial stability analysis. Daud et al. (2025) used panel QR to explore the poverty alleviation role on FDI in the case of Latin America. They showed that the results varied across quantiles.

In the case of energy economics, QR is readily used to assess the asymmetric effects for the case of energy markets and policy transmission. Tang et al. (2024) used multimethod analysis, which also included QRs and stated that the effects were varying across the quantiles. Kocak et al. (2024) and Ul-Durar et al. (2024) used the panel quantile ARDL model. Both studies show that the effects do vary across the quintiles. In the case of financial econometrics, the QR models can estimate tail-dependent effects and extreme value behaviors. This can be done by fixing the quantile position near to tails to estimate effects around the tails. Ren et al. (2022) related the carbon markets with green bonds using QonQ estimates. Their visual plots show that the estimates differed across the quantile positions. Wang et al. (2022) also estimated the quantile-based Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model and showed that financial volatility was different across quantiles.

2.3 | Comparative Assessment of Quantile Regression and OLS

Literature has also discussed the advantages and limitations of QR regression compared to OLS (Cade and Noon 2003; Chamberlain 2013; Croxford 2016). The first debate is the efficiency and context dependency of QR models. Chamberlain (2013) confirmed that QR can outperform OLS in specific contexts, especially when data exhibit quantile-specific relationships hidden in heteroskedasticity. QR further performs better when the conditional distribution varies systematically across quantiles. However, this superiority is not universal, as Croxford (2016) debated that OLS is optimal when CLRM assumptions are approximately satisfied. The second debate is whether QR is a methodological fashion or an empirical necessity. Cade and Noon (2003) showed that the use of a QR model often reflects a methodological trend rather than an empirical rationale. The ecological studies have often used QR models without demonstrating distributional heterogeneity. According to these authors, strong pretesting is required before using QR.

The preconditions of estimating QR are majorly clustered to the presence of non-normal variables in the data. However, a few studies have also pointed out that the presence of distribution-sensitive correlation between independent and dependent variables is also a strong signal towards quantile slope heterogeneity, proposing QR (Kakar et al. 2025). Other reasons can come from sampling methods, which require data collection from diverse populations or purely theoretical reasoning where extreme values are specifically studied in the behavioral context. In both cases, superficial data transformations are required in OLS to enable a model estimation, but in QR, the data sanctity can be kept.

2.4 | Challenges in Adopting QR in Dynamic and Panel Data Contexts

The extension of QR in time series and panel data contexts has broadened the scope of QR models. This extension is not free of methodological challenges. The use of fixed effect quantile regression (FE-QR) faced an incidental parameters problem, which is more prominent in nonlinear panel data models. Koenker (2004) proposed a penalized estimation approach that can shrink the coefficients, but this model is over restrictive and requires knowledge about the structure of the data. Kato et al. (2010) explored the asymptotic properties of FE-QR models. They used the bootstrap approach, which may improve the inference, but it is not universally reliable. In the case of quantile ARDL models, the identification challenges are prominent (Cho et al. 2023). Similarly, instrumental variable quantile regression (IVQR) methods try to provide consistent estimates under endogeneity, but they require careful specification and strong assumptions (Xu et al. 2021). The use of lags in the model introduces the problem of autocorrelation and endogeneity, along with the distributional heterogeneity, which limits generalizability. There is limited availability of diagnostic tools that can validate the estimation model. There are some developments, but such tools are in their early stages (Horvath et al. 2022).

2.5 | Catching up With Modern Econometrics

In the contemporary causal inference frameworks, QR has opened new methodological frontiers. One of the most important contributions is the IVQR model by Chernozhukov and Hansen (2005) to address endogeneity. This model can provide quantile treatment effects but requires strong assumptions, such as rank invariance, which may not hold in empirical contexts (Chernozhukov et al. 2020). Handling the instrumental variable in binary variables is more complex, as discussed by Wei et al. (2021), and integrating machine learning with QR regression (Arshed, Bakkar, et al. 2025)

Quantile-based different in difference (DiD) designs are showing promise but are methodologically immature. Callaway and Li (2017) discussed the quantile treatment effects (QTT). It requires assumptions that are stronger than conventional approaches, which complicates the method in panel data. Lastly, regression discontinuity designs (RDDs) are facing challenges as the QR model already allows discontinuity across quantiles (Branson and Mealli 2019).

In response to the growing literature, there is a need for assessment regardless of whether this family of estimation models can perform or provide value in econometrics. Studies in economies are increasingly acknowledging that the complexity that QR can handle can be used to extract more information from the data and assist the policymakers. Hence, this study is designed to synthesize the applications and challenges in using QRs. The study addresses the recent calls for stronger and deeper theorization in emerging fields by clarifying the functionality of QR in economics.

3 | Methodology

3.1 | Research Design

This study deploys a systematic literature review (SLR) along with supporting charts developed using bibliometric analysis to demonstrate the evolution, application, and comparative performance of QR methods in economic research. The SLR observes both the methodological development and empirical application of QR to identify key methodological branching points and cross-pollination between econometric models. Using the SLR guidelines (Okoli 2015; Paré et al. 2015), theory context characteristics and methodology (TCCM) have been used because of its ability to connect theory, context characteristics, and methodology to ensure conceptual adequacy.

3.2 | Search Strategy and Database

Primarily, the Scopus database has been used for studies between 2011 and 2025 to capture substantial methodological advancement and increased utilization of research questions in economic research. Scopus provides comprehensive coverage of economics journals that have been passed through rigorous indexing standards and robust search functionality using complex queries. The search query is designed after conducting basic research on what are the characteristics of the studies that are required for this study. The search query is as follows:

(TITLE-ABS-KEY("quantile regression" OR "median regression" OR "quantile ARDL" OR "quantile VAR" OR "panel quantile regression" OR "quantile GMM" OR "Bayesian quantile regression")) OR

(TITLE-ABS-KEY("heterogeneity" OR "distributional effect*" OR "tail behavior" OR "non-normal*" OR "robust*" OR "endogeneity" OR "asymmetric effect*")) OR

(TITLE-ABS-KEY("justification" OR "motivation" OR "reason*" OR "advantage*" OR "methodological choice" OR "empirical choice")) AND

(TITLE-ABS-KEY("economics" OR "microeconomics" OR "macroeconomics" OR "financial econometrics" OR "policy analysis")) AND

(LIMIT-TO(SRCTYPE,"j")) AND (LIMIT-TO(OA,"all")) AND (LIMIT-TO(PUBSTAGE,"final")) AND (LIMIT-TO(DOCTYPE, "ar")) AND (LIMIT-TO(LANGUAGE,"English")) AND (LIMIT-TO(EXACTKEYWORD,"Quantile Regression")) AND (LIMIT-TO(SUBJAREA,"ENER") OR LIMIT-TO(SUBJAREA,"ECON") OR LIMIT-TO(SUBJAREA,"MATH") OR LIMIT-TO(SUBJAREA,"SOCI") OR LIMIT-TO(SUBJAREA,"ENVI") OR LIMIT-TO(SUBJAREA,"BUSI"))

3.3 | Inclusion and Exclusion Criteria

The synthesis of studies is conducted using TCCM as a rule of thumb to define the inclusion and exclusion criteria. The selected studies must be reviewed, written in English, and fit the selected time period of 2011–2025. The studies must explicitly declare that they have used QR regression as a main model and provide empirical applications. The studies are also published in the domain of economics. The excluded studies are nonpeer-reviewed studies that are outside the scope of economics, studies that do not explicitly employ QR, and lastly, studies not published in English or those not available as final published papers.

3.4 | Screening and Selection Process

The screening was done using two steps. The first was the checking of the title and abstract relevance, and the second was the full text assessment. The additional quality assessment includes journal reputation, methodological rigor, clarity of reporting, and detailed use of the QR regression model. The final screening of the full text explored if the studies have explicitly discussed the merit of using QR regression as compared to OLS regression.

3.5 | Data Extraction

The study starts with the bibliometric data extraction showing selected study summary, articles across time, and a keyword cloud. The information extracted is grouped into the following domains:

- Research questions addressed using quantile regression
- Key empirical findings and their interpretation
- Comparative performance relative to OLS or other methods
- Policy implications or practical applications derived from quantile regression results
- Limitations and challenges acknowledged by authors
- Future research directions suggested

4 | Results and Discussions

Building on the description, the synthesis of QR using concept evaluation criteria by Howie and Bagnall (2020) includes intrinsic qualities, contextualization, and application. The evaluative lens positions QR as more than a statistical tool but rather a theoretically grounded approach for distribution-sensitive economic modeling.

While the search query development had shown that the QR has proliferated across many domains, there was a gap in several under-theorized constructs, which led to over-criticism on the use of QR models. Hereby, this study fills this gap by indigenous concept development of QR model utilization.

Table 1 summarizes the selected studies. There are 250 documents between 2011 and 2025. There were two duplications, 70 non-English and noneconomics, and approximately 75 of them did not have methodological rigor in explaining the contextual use of QR, along with or as a substitute for OLS. Figure 1 also shows this increasing trend.

TABLE 1 | Included studies using the PRISMA framework.

Identification	
Total using search query	250
Conference paper duplicates	3
Records after duplicates	247
Screening	
Title and abstracted to be screened	247
Excluded (not English and not from economics)	70
Records after screening	177
Eligibility	
Full texts assessed	177
Excluded (no QR debate or comparison with OLS)	75
Records remaining after eligibility	53
Final included studies	53

Source: Author self-generated.

Figure 2 visualizes the distribution of authors globally. Here we can see that the majority of the authors are from China and the United States of America (USA). Lastly, Figure 3 presents the word cloud for the keywords, showing QR as the most representative term.

After reviewing the 38 full-text studies, several themes were generated from the study. Following this chapter, all the themes are discussed one by one along with cited studies and their viewpoints.

4.1 | Theme A. Motivations for Using Quantile Regression

Primarily, QR is used to absorb the heterogeneity of effects across the distribution of the dependent variable. Unlike OLS, which assumes a homogenous marginal effect based on average, QR can reveal effects at any position, even at the tails. This flexibility allows us to explore many economic contexts such as do policy effects disproportionately benefit the poor? Do shocks have asymmetric impacts in recessions versus booms? And do extreme values in financial returns drive systemic risk?

Studies quoted in Table 2 highlight that economic processes are not uniform when considering the distribution of dependent variables. For example, Mayer et al. (2025) use the quantile Granger causality test and show that the relationships differ between lower and upper quantiles in time series data. Similarly, Ali et al. (2025) used a panel QR model to relate GDP and FDI with renewable energy; in that model, inequality and CO_2 emissions showed quantile sensitive effects. Here, the QR model shows policy heterogeneity. In an environmental

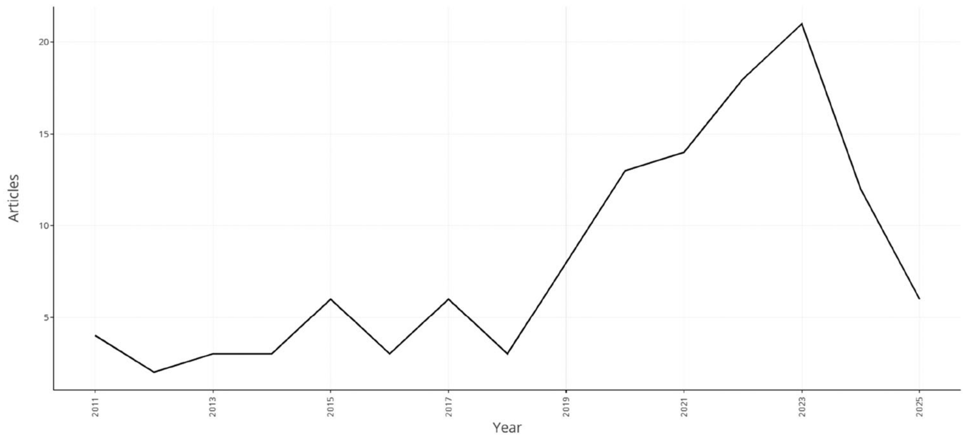

FIGURE 1 | Growth of studies discussing QR. *Source:* Author self-generated using Bibliometrix library.

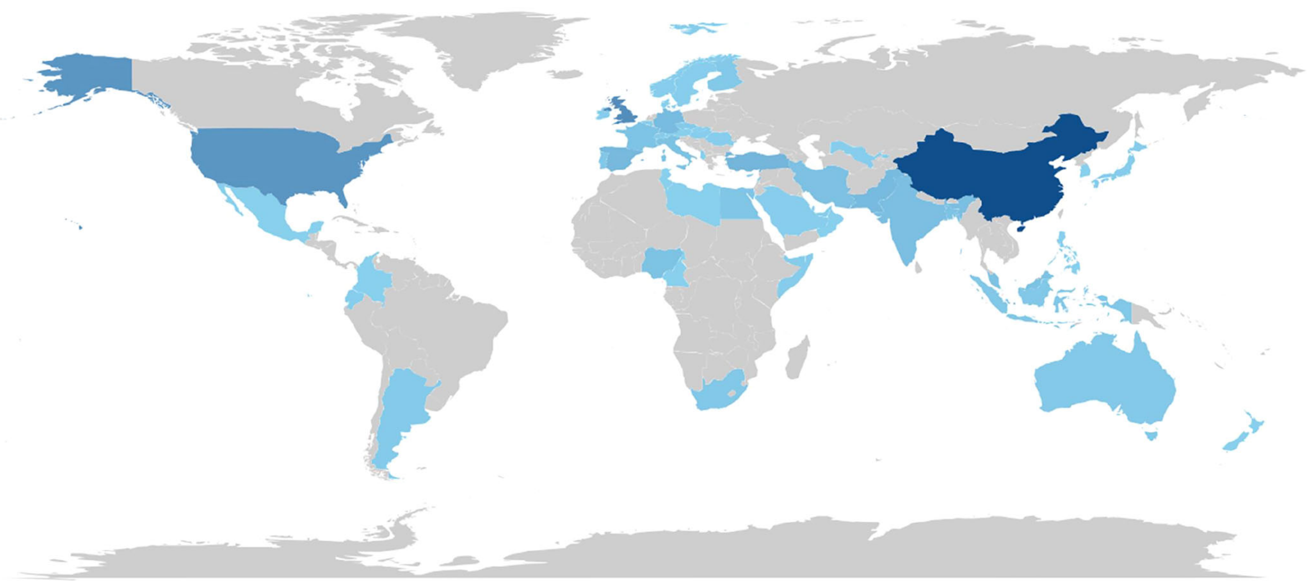

FIGURE 2 | Geographic presence of selected studies. *Source:* Author self-generated using Bibliometrix library. *Note:* The darker blue represents a higher proportion of authors from that country. [Colour figure can be viewed at wileyonlinelibrary.com]

economics context, QR can reveal that emissions and abatement costs are higher at higher quantiles, which OLS regression overlooks. Hence, QR is superior in identifying distribution-sensitive insights that OLS regression overlooks.

4.2 | Theme B. Methodological Variants of Quantile Regression

The development of a QR model had branched out to a rich methodological variant. It had increased applicability beyond the classical model of Koenker and Bassett (1978). This section has been classified into four broad variants as follows: cross-sectional QR; panel QR; time series/dynamic QR; and other specialized models like IV-QR, Bayesian QR, and machine learning QR. These innovations helped the objective in a dual way. First, it addresses identification issues like endogeneity, and second, it can make models flexible at higher dimensions.

This section categorizes the studies that demonstrate the methodological variants of QR models by increasing the complexity of economic research (in Table 3), such as cross-sectional QR used to assess inequality, corruption, and tax effects. For example, Klein and Taconet (2024) showed that QR isolates high-emission drivers at the upper tail in the cross-section case, where it is overlooked in mean regression. In the context of panel data QR, regression is used by Ali et al. (2025), and in the case of BRICS, Ojekemi et al. (2023) showed heterogenous effects across quantiles. In the case of time series, Mayer et al. (2025) use the quantile causality while Troster et al. (2018) use covariate tests for quantile forecasts. Studies are developing robust versions of quantile time series unit root tests (Bahmani-Oskooee and Ranjbar 2016; Cai and Menegaki 2019; Galvao 2009; Koenker and Xiao 2004). Kakar et al. (2025) used this model in the panel data context to handle the non-normal data. This study further integrated the asymmetric effects model, whereby this model had the capability to address asymmetric effects coming from dependent and independent variables.

FIGURE 3 | Top keywords from selected studies. *Source:* Author self-generated using Bibliometrix library. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 | Studies associated with motivations for QR.

Motivation	Relevant studies	Notes
Heterogeneous treatment effects across the distribution	Klein and Taconet (2024) and Ngepah (2024)	Poverty–growth asymmetry; emissions inequality
Robustness to non-normality and outliers	Ali et al. (2025), Amjad et al. (2021), and Li et al. (2021)	Renewable energy consumption; innovation–emissions
Asymmetry and state dependence in macro/finance	Corradi et al. (2023) and Mayer et al. (2025)	Quantile causality; conditional quantile coverage tests
Tail-focused policy insights	Bessudnov and Makarov (2015), Cheng et al. (2019), and Dai et al. (2020)	Abatement costs; environmental risks
Bayesian QR for macro stress testing	Dao and Nguyen (2025)	Showing QR's value for financial stability analysis.

Source: Author self-generated.

TABLE 3 | Studies discussing QR methodological variants.

Variant	Example studies	Notes
Cross-sectional QR	Casado-Díaz et al. (2021), Ferreira et al. (2023), and Klein and Taconet (2024)	Emissions inequality; resource policy; tourism economics
Panel QR (including MMQR)	Ali et al. (2025), Iqbal et al. (2024), Kakar et al. (2024, 2025), Li et al. (2021), and Ojekemi et al. (2023)	Renewable energy determinants; BRICS sustainability; innovation–emissions
Time-series/Dynamic QR	Corradi et al. (2023), Dai et al. (2020), and Mayer et al. (2025)	Quantile causality under instability; coverage tests; abatement cost modeling
Instrumental variables QR (IV-QR)	Chernozhukov et al. (2015) and Fidrmuc and Fidrmuc (2016)	Identification in endogenous regressors
Bayesian and ML-integrated QR	Machado and Santos Silva (2019) and Zhang et al. (2019)	Quantiles via moments (QvM); QR-based clustering
Quantile treatment with in DiD	Callaway and Li (2017)	Demonstrating recent expansion of QR in causal inference frameworks
Quantile on quantile models	Hassan et al. (2021)	Studies compared the distribution heterogeneity of dependent and independent variables
Convex QR and specialized estimators	Conde-Amboage et al. (2015) and Dai et al. (2020)	Convex regression for abatement costs; computational advances

Source: Author self-generated.

TABLE 4 | Studies associated with application domains.

Domain	Example studies	Focus
Microeconomics	Balcilar et al. (2022), Casado-Díaz et al. (2021), Ferreira et al. (2023), and Ngepah (2024)	Poverty–growth asymmetry; resource use inequality; tourism economics; labor productivity
Macroeconomics	Arshed and Hassan (2021), Corradi et al. (2023), Dai et al. (2020), Hassan et al. (2021), Mayer et al. (2025), and Zhang et al. (2019)	Quantile causality; conditional quantile forecasts; abatement costs; panel clustering in macro panels
Business economics	Hameed et al. (2023)	Estimated the entrepreneurship determinants across countries and time
Finance	Chen (2023), Kumail et al. (2025), Pereda-Fernández (2024), Riaz et al. (2025), Ul-Durar, Bakkar et al. (2025), and Yamada (2023)	Commodity market asymmetries; quantile VAR in finance; stock return determinants
Energy/Environment	Ali et al. (2025), Arshed et al. (2024), Arshed, Iqbal et al. (2025), Cheng et al. (2019), Dutta et al. (2021), Klein and Taconet (2024), Li et al. (2021), Ojekemi et al. (2023), Tanveer et al. (2025), Ul-Durar, De Sisto et al. (2025), and Wang et al. (2021)	Renewable energy drivers; BRICS sustainability; innovation–emissions link; environmental risk; mobility emissions inequality

Source: Author self-generated.

Specialized QR models have been introduced in the literature. The instrumental variable (IV-QR) model was the first one to address endogeneity. This model was used in the study on labor, education, and development (Chernozhukov et al. 2015; Fidrmuc and Fidrmuc 2016). Finally, the convex method used by Dai et al. (2020) indicated complex computational designs and showed how QR models can handle large data sets and complex economic problems. Across these variants, there is a clear trend that QR models have evolved into a robust model. These innovations are not exhaustive; rather they are interconnected and can help in making better models.

4.3 | Theme C. Domains of Application of Quantile Regression

QR models are being readily applied across diverse fields, such as economics because of their flexibility. Within economics, these studies are further divided into the following four major domains: microeconomics, macroeconomics, finance, and energy/environmental economics. The discussion on each domain shows how QE models demonstrate value.

Table 4 provides the studies categorized in the application domain. QR has been used to explore poverty's asymmetric response to growth and inequality (Ngepah 2024). Results show that poverty reduction is concentrated in middle quantiles, while the poorest households benefit less, especially under high inequality. In labor markets and resource economics, QR reveals heterogeneous impacts of productivity policies and resource extraction, showing that average estimates understate effects in vulnerable groups (Balcilar et al. 2022; Ferreira et al. 2023). Casado-Díaz et al. (2021) used QR in tourism economics to uncover nonlinear tourism demand effects, which can provide efficient pricing and seasonality strategies.

In macroeconomics, the QR model is flexible in allowing asymmetric effects across economic cycles. Mayer et al. (2025) show how quantile causality captures predictive relations under instability, with stronger causality in recessions than expansions. Troster et al. (2018) developed coverage tests for conditional quantiles, improving forecast evaluation for growth-at-risk frameworks. Convex QR approaches (Dai et al. 2020) estimate abatement costs across quantiles, providing policy-relevant distributions of climate mitigation costs.

QR has been widely used in financial economics to analyze risk-return dynamics. For instance, in commodity markets (Chen 2023), QR highlights asymmetric responses of prices to global shocks, with tail risks especially pronounced in resource-dependent economies. Similarly, studies in financial econometrics (Pereda-Fernández 2024; Yamada 2023) show that returns and volatilities often display quantile-specific determinants, such as firm leverage or macro news shocks, challenging OLS-based portfolio strategies. Kumail et al. (2025) used this model to estimate the money demand while allowing the data to have extreme values.

This is the most prolific application domain. Ali et al. (2025) used panel QR to show that GDP and FDI promote renewable energy consumption, but the effect of inequality and emissions is quantile-dependent. A study of BRICS economies (Ojekemi et al. 2023) found that renewable energy's contribution to sustainability is stronger in higher quantiles, suggesting that advanced economies benefit disproportionately. QR has also revealed nonlinear links between innovation and emissions (Li et al. 2021)

TABLE 5 | Studies that compared QR with OLS.

Comparative insight	Example studies	Notes
Sign reversals across quantiles	Klein and Taconet (2024) and Ngepah (2024)	Poverty–growth relation flips in tails; emissions drivers differ by quantile
Effects only visible in tails	Cheng et al. (2019) and Dai et al. (2020)	Abatement costs and environmental damage emerge only in upper quantiles
OLS underestimates heterogeneity	Ali et al. (2025), Goswami et al. (2021), and Ojekemi et al. (2023)	REC drivers vary by quantile; BRICS sustainability impacts stronger in upper quantiles
Forecasting and causality	Corradi et al. (2023) and Mayer et al. (2025)	QR-based causality and coverage tests outperform mean-based tests
Policy implications differ	Ferreira et al. (2023) and Li et al. (2021)	Innovation–emissions links nonlinear; resource inequality underestimated by OLS

Source: Author self-generated.

and quantified tail risks in environmental damages (Cheng et al. 2019). Finally, mobility emissions in Germany (Klein and Taconet 2024) highlight inequality among emitters, with high-quantile drivers responsible for disproportionate emissions—a critical policy insight. Ren et al. (2022) related carbon markets and green bonds using QonQ regression to illustrate tail-dependent risk in sustainable finance.

Across domains of economic research, QR can observe the presence of distributional heterogeneity to support theory and policy. QR contributes to the heteroskedastic assessment of growth and inequality effects across income groups in microeconomics. QR contributes to estimates of heteroskedastic causal estimates in macroeconomics. QR can enrich the risk and return understanding related to extreme cases in finance. QR can estimate the heterogenous emissions to energy use relationship in environmental economics. All these complex estimates can help in making situation-driven policy insights. This section responds to the SLR objective to identify how QR can make distribution-centric policy design, and OLS only provides an average response.

4.4 | Theme D. Comparative Insights: Quantile Regression Versus OLS

One part of SLR is to differentiate QR and OLS in terms of the ability to extend policy insights. The studies presented in Table 5 advocate that QR does more than mere replication of OLS; rather, it can increase the interpretability of economic relationships that can uncover heterogeneity, behavior at tails, and sign reversals.

Table 5 provides studies that compared OLS with QR. OLS often obscures heterogeneity by producing an average effect that may not hold across the distribution. For example, the South African poverty study (Ngepah 2024) shows that growth reduces poverty in middle quantiles but has negligible or even negative effects at the lowest quantiles under high inequality. Similarly, in the German mobility emissions study (Klein and Taconet 2024), OLS suggests uniform drivers of emissions while QR reveals that high-quantile emitters respond differently to policy variables.

Several studies demonstrate that relationships are only visible at the distribution tails. Convex QR models of abatement costs in China (Dai et al. 2020) show that marginal abatement costs increase sharply in the upper quantiles, a pattern missed by OLS. Environmental risk analyses (Cheng et al. 2019) similarly reveal that the most severe damages are concentrated in extreme quantiles, underscoring the importance of tail-focused policy design.

Panel QR studies in renewable energy consumption (Ali et al. 2025) and BRICS sustainability (Ojekemi et al. 2023) show that OLS averages conceal the stronger impacts observed in upper quantiles, such as high-income economies benefiting more from renewable investments. These results demonstrate that OLS systematically understates inequality in effects.

Dynamic QR approaches outperform mean-based methods in capturing state-dependent dynamics. Mayer et al. (2025) show that QR-based Granger causality detects predictive relationships that OLS fails to uncover under instability. Similarly, Troster et al. (2018) propose conditional quantile coverage tests, which more effectively evaluate distributional forecast accuracy than traditional mean-squared error metrics.

The divergence between OLS and QR findings is not merely statistical—it translates into different policy recommendations. For example, innovation's effect on environmental quality in China (Li et al. 2021) follows an inverted-U pattern that is only evident in specific quantiles, suggesting nuanced policy interventions across industries. Similarly, QR studies of resource inequality (Ferreira et al. 2023) demonstrate that interventions targeting average effects may neglect those most at risk.

Conclusively, when comparing QR with OLS, the average-based estimate in OLS hides many subcluster behaviors because of the normality assumption. QR can explore distribution-centric effects and identify the subclusters where the relationship varies or reverses. This section addresses another objective of highlighting the superiority of QR estimates in terms of increased contextuality in economics, finance, and environmental outcomes.

TABLE 6 | Studies that discussed the validation and robustness.

Validation/Robustness approach	Example studies	Notes
Bootstrap inference for QR estimates	Chen (2023), Huang et al. (2023), Li et al. (2021), and Mayer et al. (2025)	Applied to causality tests, commodity shocks, and innovation–emissions models
Conditional quantile coverage tests	Corradi et al. (2023) and Dai et al. (2020)	Out-of-sample forecast evaluation for growth-at-risk and abatement costs
Sensitivity to structural breaks and instability	Conde-Amboage et al. (2015) and Mayer et al. (2025)	Structural stability analysis in quantile causality and computational estimation
Placebo or falsification checks	Ferreira et al. (2023) and Klein and Taconet (2024)	Tests of robustness of resource policy impacts and emissions drivers
Model comparison across quantiles vs. mean	Ngepah (2024), Ojekemi et al. (2023), and Wang et al. (2024)	Poverty–growth asymmetry and sustainability analysis in BRICS economies

Source: Author self-generated.

4.5 | Theme E. Validation and Robustness Practices in Quantile Regression Studies

Studies in survey design or longitudinal panel data focus more on the robustness of estimates and require more evidence using diagnostics, sensitivity, and subsample analysis. QR can provide a complete package in one model and can provide a single estimate on medians, which can resemble mean-based OLS if the data are normal but can also then be expanded to see distributional effects if the data are not normal. Table 6 provides reviews of studies where bootstrap inference, convergence tests, sensitivity tests, and falsification strategies validate findings within QR. These extensions of QR enable this model to become statistically reliable and reproducible in economic research.

Table 6 categorized the studies that provided robust analysis with QR. Due to QR estimators not assuming homoskedasticity, bootstrapping is a standard tool for inference. In time-series settings, Mayer et al. (2025) use bootstrapped quantile causality tests to ensure robustness under instability. Similarly, studies of commodity price shocks (Chen 2023) apply block bootstrap procedures to validate tail effects in volatile data. Innovation–emissions models in China (Li et al. 2021) use bootstrapped confidence intervals to account for distributional skewness.

Recent advances have introduced direct tests for conditional quantile adequacy. Troster et al. (2018) develop out-of-sample tests to evaluate whether forecast distributions adequately capture tail behavior—a critical step for macro-financial models, such as growth-at-risk. Convex QR applications in environmental economics (Dai et al. 2020) similarly use coverage tests to validate abatement cost estimates, ensuring robustness across quantiles.

Dynamic QR applications explicitly test for robustness to structural breaks. Mayer et al. (2025) demonstrate that causality results differ significantly when ignoring instability, underscoring the importance of incorporating structural shifts. Computational studies (Conde-Amboage et al. 2015) show that instability can bias parameter estimates if not addressed with appropriate quantile algorithms.

To confirm causal interpretations, some QR studies employ placebo regressions. Resource inequality research (Ferreira et al. 2023) introduces falsification tests to show that tail effects do not appear in unrelated sectors, bolstering credibility. In environmental economics, German emissions inequality studies (Klein and Taconet 2024) test alternative drivers (e.g., demographics) to rule out spurious associations.

Several studies explicitly compare QR with OLS to validate added value. Poverty–growth research in South Africa (Ngepah 2024) shows that OLS underestimates tail effects, while panel QR in BRICS economies (Ojekemi et al. 2023) demonstrates that sustainability linkages strengthen in higher quantiles. These comparisons validate QR's superiority in capturing heterogeneity.

Robustness practices are not ancillary but central to the credibility of QR studies. The consistent use of bootstrapping, coverage tests, and falsification strategies demonstrates an emerging best practice standard in applied QR research. These practices directly address the methodological objective of this SLR: ensuring that quantile-based insights are not artifacts of estimation but represent genuine distributional heterogeneity with policy significance.

4.6 | Theme F. Limitations and Pitfalls of Quantile Regression in Economics

Despite its advantages, the literature highlights several recurring challenges in applying QR. These limitations relate to interpretability, sparse data at distribution tails, multiple-testing risks, and computational complexity. While these do not undermine QR's value, they signal important caveats for empirical researchers and highlight areas for methodological improvement.

A key limitation is that QR estimates the effect of covariates on conditional quantiles of the outcome, not on subgroups of the population (listed in Table 7). A study by Li et al. (2021) indicated the presence of nonlinear effects across quantiles, but the estimation setup does not allow differentiation between effects for low-emission firms and high-emission firms. Similarly, resource

TABLE 7 | Studies discussing QR limitations.

Limitation	Example studies	Notes
Interpretability of conditional quantile effects	Ferreira et al. (2023) and Li et al. (2021)	Effects describe conditional quantiles, not subgroup averages
Sparse tails/Unstable estimates	Cheng et al. (2019) and Dai et al. (2020)	Environmental damage and abatement costs sensitive to thin data in extremes
Multiple quantiles testing inflation	Conde-Amboage et al. (2015) and Corradi et al. (2023)	Forecast coverage and computational studies note elevated false positives
Computational cost in high-dimensional or dynamic QR	Machado and Santos Silva (2019) and Zhang et al. (2019)	Quantiles via moments and QR clustering developed partly to mitigate computational bottlenecks

Source: Author self-generated.

inequality analyses (Ferreira et al. 2023) highlight that conditional quantile effects may not map neatly onto demographic or structural groups, complicating policy translation.

Many empirical data sets are not large enough to have thicker tails. Studies in the domain of environmental economics and climate change point out that the estimates in the 5th and 95th quantiles are unstable (Cheng et al. 2019; Dai et al. 2020). Having multiple quantile estimates in QR may also lead to false positives. Corradi et al. (2023) stated that quantile convergence tests are required to ensure that the estimates are not spurious. A similar issue pointed out by Conde-Amboage et al. (2015) stated that having many quantiles leads to a higher type I error.

Making high-dimensional and dynamic QR models requires computational ability along with large data. This challenge is being addressed by new algorithms to estimate QRs. One of the solutions is quantiles via moments, proposed by Machado and Santos Silva (2019), that enables estimation of slope coefficients using the method of moments. Estimating QR is also necessitated by the presence of known or unknown subclusters in the data. The models that can estimate clusters have not reached maturity.

Empirically, QR has shown its ability to extend insights, but it is not free from limitations. Thinner tails may lead to unstable estimates, as QR regression requires multiple validation support that can lead to false positives. Recent advancements like IV-QR regression are mitigating some issues. The identification of challenges related to QR helps in achieving SLR objectives.

4.7 | Theme G. Future Research Directions in Quantile Regression

The studies in our review not only apply QR but also highlight important gaps and opportunities for methodological and applied research. Future directions can be grouped into four clusters as follows: (1) causal QR at scale, (2) dynamic and nonlinear QR, (3) high-dimensional and ML-assisted QR, and (4) policy design for distributional targeting.

Several methodological papers argue that while QR identifies distributional associations, stronger causal frameworks are needed (shown in Table 8). IV-QR (Chernozhukov et al. 2015; Fidrmuc and Fidrmuc 2016) provides a foundation, but applications remain limited. Future work could integrate QR with difference-in-differences or RDDs to study distributional treatment effects. For instance, poverty–growth asymmetry studies (Ngepah 2024) call for causal identification strategies to move beyond descriptive heterogeneity.

There are also recent developments in structural equation modeling that are adapting to quantile-based estimates to allow non-normal survey data analysis (Cheng 2024; Wang et al. 2016). Macroeconomic and financial applications highlight the importance of state dependence. Mayer et al. (2025) suggest extending quantile causality to time-varying and regime-switching frameworks, especially in volatile markets. Coverage tests show the need for models that adapt to structural breaks and nonlinearities, while abatement cost studies highlight the complexity of forecasting tail behavior under policy shocks.

With the increase in available datasets and computational ability, researchers are able to evolve the estimation models that can address data complexity. The quantile method of moments model is one of the innovations that allows addressal of endogeneity in QR. Zhang et al. (2019) used QR-based clustering method to identify distributional groups in the dependent variable. Computational innovation provided by Conde-Amboage et al. (2015) showed the potential for estimating QR with penalized coefficients to address multicollinearity.

The ability to estimate tail-focused interventions advocates the need for QR regressions. Empirical studies allow this aspect to target the top emitters and learn from the least emitters. BRICS sustainability research (Ojekemi et al. 2023) shows that renewable energy's contribution is strongest in high quantiles, suggesting that wealthier economies may benefit more unless redistribution mechanisms are designed. Innovation–emissions studies call for differentiated policies across industries, while environmental risk analyses (Cheng et al. 2019) emphasize focusing on extreme-risk scenarios.

Future research directions highlight a dual trajectory: (i) methodological deepening through causal inference, dynamic extensions, and machine learning integration, and (ii) applied broadening through distribution-sensitive policy evaluation. In the case of methodological deepening, QR models must also diversify in terms of pre-and post-estimation tests to validate the estimates. EViews provides multiple tests, like quantile-wise slope plots

TABLE 8 | Studies discussing further directions for QR model.

Future research direction	Example studies	Notes
Causal QR (IV-QR, QR-DiD, treatment heterogeneity)	Chernozhukov et al. (2015), Fidrmuc and Fidrmuc (2016), and Ngepah (2024)	Expanding credible identification in QR; combining with difference-in-differences
Dynamic and nonlinear QR (time-varying, regime-switching)	Corradi et al. (2023), Dai et al. (2020), and Mayer et al. (2025)	Need for QR models that adapt to structural breaks, volatility regimes, and tail risk
High-dimensional and ML-assisted QR	Arshed, Bakkar et al. (2025), Conde-Amboage et al. (2015), Machado and Santos Silva (2019), and Zhang et al. (2019)	Integration with machine learning (LASSO, clustering, neural nets); efficient computation
Policy design for tails (distribution-sensitive policy evaluation)	Cheng et al. (2019), Klein and Taconet (2024), Li et al. (2021), and Ojekemi et al. (2023)	Applying QR to inform targeted climate, energy, and social policies

Source: Author self-generated.

and slope asymmetry tests that can be adopted across other software packages. Software packages like STATA and Gauss are innovating in this domain to increase the practicality of this model. Tests can be developed to estimate the distribution sensitivity of the model by comparing QR and OLS estimates, and the determination of unknown statistically heterogenous clusters can be determined by comparing slope differences across quantiles of dependent variables.

These directions align strongly with the objectives of this SLR—to chart not only what QR has achieved but also where it can extend economic analysis in the coming years. This study also extracted a theme that describes the future research directions using QR. It is identified that QR can be used for causal identification, regime-switching models, and machine learning for high-dimensional data.

This review emphasizes that the methodological advancement of QR can extract actionable insights into policy and managerial decision-making in the context where distributional inequality risks are prevalent. Figure 4 summarizes the outcome of the study.

5 | Conclusion

This study synthesizes the theoretical and empirical foundations for quantile-based estimation models that can extend econometric research. The objectives were achieved by partitioning different aspects of QR regression models. The thematic synthesis across these dimensions highlighted that QR enables deeper insights using distributional heterogeneity, tail-specific effects, and robust outcomes. The study used genealogical discussion, bibliometrics analysis, and the SLR method, and specified their research objectives.

This summarized the increasing family of QR models by enlisting cross-sectional QR for social analysis, panel QR for heterogenous panels with instruments using MMQR. Dynamic QR modeling for time series macroeconomics and specialized extensions, such as IV-QR and quantiles, via moments for causal and high-dimensional contexts. The methodological advances can handle major post-regression concerns like endogeneity, nonlinearity, and computational complexity.

The empirical works cited QR as a versatile model across microeconomics, macroeconomics, finance, and the environment. There are studies on poverty–growth asymmetric relationships in microeconomics, quantile-wise causality in macroeconomics, tail-dependent risk dynamics in finance, and emissions inequality in environmental economics. In all cases, QR regression contributes to distribution-centric policy design.

The major highlight is that QR regression led to substantive conclusions compared to OLS. OLS assumed that the estimates are independent of data positioning, which underscores limitations to OLS where the effects are distribution-centric. QR can adapt to bootstrapping, quantile convergence, and sensitivity analysis. Using this QR, regression reveals the distributional patterns rather than assumption-based mean-effects. This study also presented the challenges in QR models. First is the interpretation of quantile-based effects; and adaptation to these multiple coefficients will be a challenge for policy makers. It would require adaptive policy design. The data requirements are higher in QR so that it can estimate the effects on tails. High-dimensional QR models required computational power. There is a lack of post-estimation diagnostics available for QR models.

There are two important points highlighted by the study. First is the methodological deepening created by IV-QR, QR-DiD, and integration with machine learning. Second is the application broadening, which provides policies optimized to the distribution context, which, in turn, helps in ensuring an improvement in policy effectiveness by targeting each subcluster rather than one size fits for all in OLS.

The SLR had helped in classifying the implications of QR modeling in economics. We are able to highlight several important implications. QR has the ability to theoretically enrich economic theory that now provides heterogenous, asymmetric, and state-dependent effects. QR models are methodologically evolved models that are flexible in handling cross-sectional, time series, and panel data in economics. Policymakers can not retrofit their

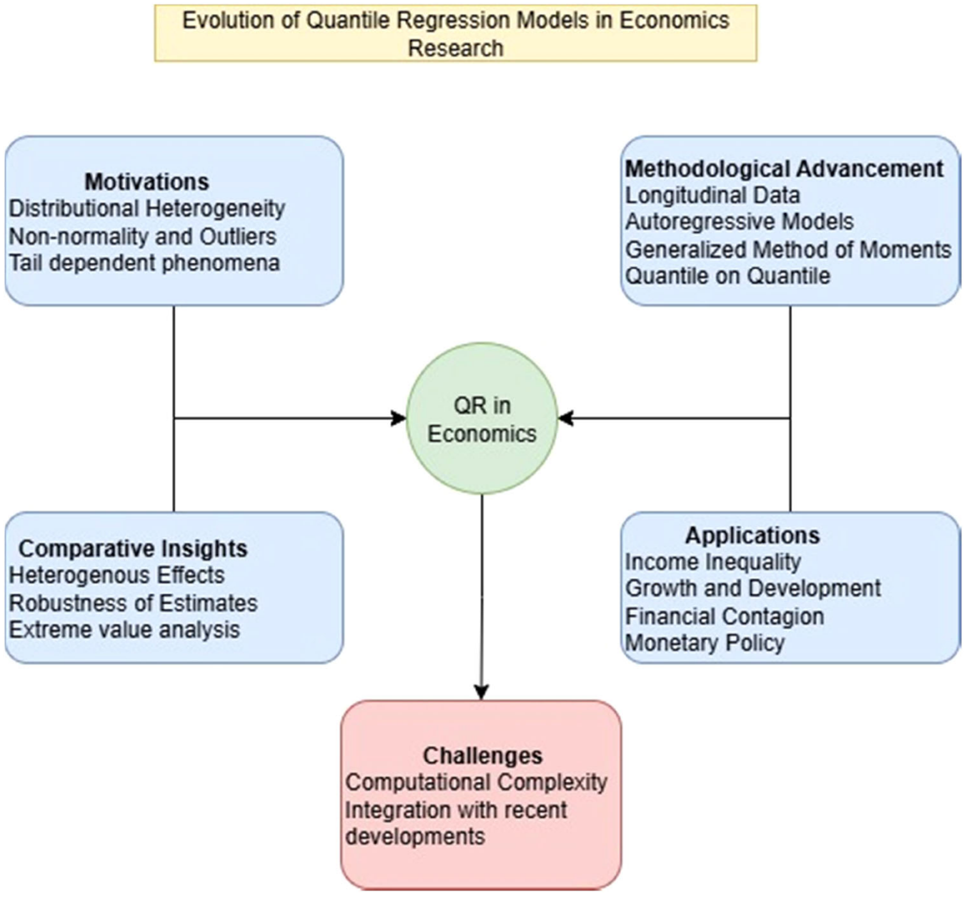

FIGURE 4 | QR models and their implications. *Source:* Author self-generated. [Colour figure can be viewed at wileyonlinelibrary.com]

policies, which are not overly generalized for the population; rather, they identify subclusters and suggest modifications.

The illustration of the QR model is not free of estimation challenges. There are concerns like interpretability, sparse tails, increased testing processes, and computation requirements. Hence, though there are advances, there is still a big gap to fill, which makes QR a computationally sound model. This study advocates that QR is not a replacement for OLS but a complementary econometric tool that can explore specificity within theoretical and empirical generalization established by OLS. On one hand, OLS can find aggregate behaviors QR explores distributional variations. This perspective can help economists improve the area under the curve estimation with precision by using nonlinear curve estimation. The study is instrumental in proposing hybrid modeling using QR and OLS estimates.

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Ethics Statement

The entire research process is in line with our institutional research ethics policy. We declare that all ethical standards are met and complied with in true letter and spirit.

Consent

No consent was required as the paper is based on secondary data.

Conflicts of Interest

The authors declare no conflicts of interest. It is to affirm that the work is not submitted anywhere else other than this journal.

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