Methodological Advances in Microdata Imputation: Quantile Regression Forests for Wealth Imputation

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Abstract

This paper evaluates the methodological advantages of Quantile Regression Forests (QRF) for wealth imputation between the Survey of Consumer Finances (SCF) and Current Population Survey (CPS). We demonstrate that QRF outperforms traditional imputation approaches by preserving conditional distributions rather than merely conditional means, a critical distinction when handling highly skewed wealth data. Our empirical analysis, implemented through the Microimpute package, provides evidence that QRF reduces bias in wealth distribution estimates, achieving a 21-22% reduction in average quantile loss compared to OLS and hot deck matching. Using 5-fold cross-validation on 22,975 SCF households, QRF maintains an average quantile loss of 0.059 across all quantiles, demonstrating superior distributional accuracy, particularly in the critical 20th-80th percentile range. While we focus on wealth, QRF's advantages extend to any skewed variable requiring distributional preservation, including consumption, medical expenses, and other heavy-tailed economic measures. These technical improvements have substantial implications for wealth inequality research and microdata enhancement. We release our open-source Microimpute package to facilitate microimputation across the field, providing automated method comparison, hyperparameter tuning, and survey weight integration capabilities that streamline the imputation workflow for complex survey data.

1 Introduction

Microsimulation models and detailed microdata analyses are essential tools for understanding the distributional impacts of policies and social changes. These analyses require data that accurately represent both the demographic composition of a population and its economic circumstances. However, available data sources, particularly large-scale surveys, often suffer from missing data due to unit or item nonresponse (Dempster and Rubin, 1983). If not appropriately addressed, missing data can introduce substantial bias and reduce statistical power, undermining the validity of research conclusions (Graham, 2009). This problem is

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especially acute for complex variables like household wealth, which are often characterized by high skewness, influential outliers, and significant nonresponse for sensitive items (Barceló, 2008). UK evidence confirms these challenges: the Office for National Statistics acknowledges that household surveys struggle to capture the incomes of the very richest individuals, particularly those in the top 1% (Office for National Statistics, 2019), while the Institute for Fiscal Studies estimates that nearly £800 billion of wealth held by the wealthiest UK households is missing from survey data (Crawford et al., 2016). Furthermore, declining survey response rates—falling from 49% pre-pandemic to 31% in recent years—compound these measurement challenges (Institute for Fiscal Studies, 2025).

Traditional imputation approaches struggle with wealth data's extreme right-skewness, heavy tails, and complex non-linear relationships with demographic and economic predictors. These characteristics fundamentally violate assumptions underpinning conventional methods like Ordinary Least Squares (OLS) and Quantile Regression, resulting in significant distortions that undermine policy analysis (Meinshausen and Ridgeway, 2006).

This paper demonstrates that Quantile Regression Forests (QRF) provides superior performance for wealth imputation between the Survey of Consumer Finances (SCF) and the Current Population Survey (CPS). By modelling entire conditional distributions rather than conditional means alone, QRF preserves critical distributional features of wealth data. We implement this approach through the Microimpute package, a specialised tool developed for survey data imputation that provides a complete pipeline for imputation and analysis, tailored to the dataset at hand.

The remainder of this paper is organized as follows: Section 2 reviews the statistical properties of wealth microdata and the evolution of imputation techniques in the literature. Section 3 describes our data sources (SCF and CPS) and their characteristics. Section 4 presents the QRF methodology and the Microimpute package in detail. Section 5 presents our empirical results. Section 6 discusses implications and limitations, and Section 7 concludes. Our analysis makes two key contributions:

- An open-source microimputation package that facilitates the evaluation of multiple imputation methods tailored to specific dataset needs
- A validation framework comparing novel methodological approaches to traditional imputation methods demonstrated on statistically challenging data like wealth distributions

2 Background

Effective imputation requires understanding both the data's nature and the available techniques. This section first explores the statistical properties of wealth microdata that challenge imputation. It then reviews the literature on microdata imputation methods, tracing their development and practical applications.

2.1 Statistical properties of wealth distributions and imputation challenges

Wealth microdata present unique statistical challenges that can render standard imputation methods ineffective.

1. **High skewness and concentration**: Wealth distributions are typically right-skewed, with a small percentage of households holding a large share of total net worth (Chen et al., 2020). This concentration means that imputation models assuming normality can perform poorly, biasing estimates of wealth aggregates and inequality (Lun and Khattree, 2019).

2. **Outliers and extreme values**: Legitimate extreme values are common and can unduly influence parametric imputation models. Robust methods or data transformations are often necessary (Chen et al., 2020).

3. **Non-linear relationships**: Wealth's relationship with predictor variables such as age, education, and income is highly non-linear (Zillow Group, 2024), requiring more flexible imputation methods.

2.2 Traditional microdata imputation methods

Among traditional imputation methods, we have selected three to dive into, namely Ordinary Least Squares regression, Quantile regression, and Statistical matching, due to their diverse approaches to imputation and relevance in the literature. We also study more novel approaches like Quantile Regression Forests, which provides an opportunity for more robust microdata imputation.

2.2.1 Ordinary Least Squares (OLS)

OLS imputation predicts missing values in a recipient dataset based on a linear regression model trained on a donor dataset. The model is specified as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_p x_{ip} + \varepsilon_i,$$

where y_i is the variable to be imputed for observation i in the recipient dataset, x_{i1},...,x_{ip} are predictor variables common to both donor and recipient datasets, β_0,...,β_p are coefficients estimated from the donor dataset, and ε_i is the error term (Bruch, 2023). In deterministic regression imputation, the imputed value is typically the expected value of y_i. An alternative, stochastic regression imputation, adds a randomly drawn residual (from the donor model's residuals or a normal distribution with estimated variance σ^2) to the predicted value: $y_{imputed} = y^i + e_i$, where e_i $N(0, \sigma^2)$. Stochastic imputation aims to preserve the variability of the original data better than deterministic imputation (Anil).

OLS assumes linearity, homoscedasticity (constant variance of errors), and normally distributed errors, all of which are typically violated by skewed wealth data (Von Hippel, 2007). OLS commonly underperforms when imputing microdata as it tends to underestimate high wealth values and overestimate low values, thereby flattening the true distribution (Woodruff, 2023). While OLS imputation might yield consistent estimates for means and variances even with non-normal data, it can produce considerable bias for shape-dependent estimands like percentiles or skewness coefficients (Von Hippel, 2007). Furthermore, deterministic OLS imputation systematically underestimates the true variance of the completed data (Barceló, 2008).

2.2.2 Quantile Regression (QR)

Quantile regression (QR) models the conditional quantiles (e.g., median, 10th percentile, 90th percentile) of a response variable, Y, given a set of predictors, X (Koenker and Bassett, 1978). The model for the τ-th quantile is:

$$Q_Y(\tau|X) = \beta_0(\tau) + \beta_1(\tau)x_1 + \beta_2(\tau)x_2 + ... + \beta_p(\tau)x_p$$

When inputting from a donor to a recipient dataset, QR models for various quantiles τ are fitted on the donor dataset using common predictor variables. These fitted models are then applied to the recipient dataset to predict the conditional quantiles for observations with missing data (Parker). To generate a single imputed value, one might impute the conditional median ($\tau = 0.5$) or draw a value from an estimated conditional distribution constructed from multiple quantile predictions (Wei et al., 2014). For instance, a random quantile $\tau*$ can be selected from a uniform distribution, and the imputed value computed by interpolating between the estimated responses for quantiles directly above and below $\tau*$ (Chen and Yu, 2007).

QR is more robust to outliers and better at handling skewed distributions and heteroscedasticity than OLS because it does not make strong assumptions about the error distribution (Zhao et al., 2023). This makes it particularly suitable for economic variables like wealth, where relationships may vary across the distribution, better preserving its overall shape (Kleinke and Reinecke, 2020). However, while more robust than OLS, standard quantile regression still assumes linear relationships between predictors and the outcome at each specific quantile (Meinshausen and Ridgeway, 2006). It requires fitting separate models for different quantiles, which can increase complexity, and may struggle with high-dimensional data or very complex non-linear patterns (Meinshausen and Ridgeway, 2006).

2.2.3 Hot deck Matching imputation

Hot deck imputation replaces missing values in a recipient record with an observed value from a "similar" donor record. When imputing from a donor dataset to a recipient dataset, "similarity" is established using variables common to both datasets (D'Orazio et al., 2021). This often involves:

1. **Defining adjustment cells (grouping)**: Records in both datasets are grouped into cells based on shared categorical variables (e.g., age group, education level). Donors are then selected from the corresponding cell in the donor dataset (Chen and Shao, 2000).

2. **Nearest Neighbor Matching**: For continuous or mixed data, a distance metric (e.g., Euclidean, Mahalanobis) is calculated between a recipient record and potential donor

records based on common variables. The donor record with the smallest distance is chosen (D'Orazio et al., 2021). The actual value from the selected donor record in the donor dataset is then used to fill the missing item in the recipient dataset (Andridge and Little, 2010).

Hot deck methods are non-parametric and do not require explicit model specification, making them robust to weak distributional assumptions (D'Orazio et al., 2021). Since imputed values are actual observed values from the donor dataset, they are inherently plausible and can help preserve the marginal distribution of the imputed variable if donors are well-matched (Andridge and Little, 2010). Nonetheless, a critical challenge is ensuring an adequate and representative donor pool in the donor dataset for all types of recipients in the target dataset. This is particularly difficult for extreme wealth values, where suitable donors may be scarce or unrepresentative, leading to biased imputations or overuse of certain donors (Haziza, 2009). Additionally, it may struggle to maintain complex multivariate relationships, especially when imputing across datasets with potentially different underlying structures or sampling designs (Siddique and Belin, 2008). The effectiveness is highly dependent on the choice of matching variables (Office of Tax Analysis, 2012), as well as "similarity" metrics. Poorly defined cells or metrics can lead to inappropriate donor selection and biased results (Andridge and Little, 2010).

2.2.4 Quantile Regression Forests (QRF)

Quantile Regression Forests (QRF) (Meinshausen and Ridgeway, 2006) extend Random Forests (RF)—ensemble learners that build multiple decision trees and excel at capturing non-linearities and interactions (Breiman, 2001)—to estimate conditional quantiles. When imputing from a donor dataset to a receiver dataset, QRF models are trained on the donor dataset using predictor variables common to both. Instead of storing only mean values in terminal nodes (as in standard RF regression), QRF retains all observed outcome values for the training instances that fall into each terminal leaf of each tree (Meinshausen and Ridgeway, 2006).

For a given point x (representing the predictor values for an observation in the recipient dataset), the conditional distribution function $\hat{F}(y|X = x)$ of the target variable Y is estimated as:

$$\hat{F}(y|X = x) = \sum_{i=1}^{n} w_i(x) \cdot \mathbf{1}_{Yi \leq y},$$

where Y_i are the observed values from the donor dataset, $1_{Yi} \leq y$ is an indicator function (1 if $Yi \leq y$, 0 otherwise), and $w_i(x)$ represents the weight assigned to each donor observation i. This weight is derived from the forest structure; specifically, $w_i(x)$ is positive if observation i from the donor set falls into the same terminal node as x in any tree, and its magnitude reflects how often this co-occurrence happens across all trees in the forest (Kleinke and Fritsch, 2023).

The τ-th conditional quantile is then estimated by finding the infimum value y for which the estimated cumulative distribution function $\hat{F}(y|X = x)$ is greater than or equal to τ:

$$\hat{Q}_\tau(y|X = x) = \inf y : \hat{F}(y|X = x) \geq \tau$$

(Meinshausen and Ridgeway, 2006). This allows for the estimation of any quantile without retraining the model (Woodruff and Ghenis, 2024). For imputation, particularly multiple imputation, values can be drawn randomly from this estimated conditional distribution for each observation in the recipient dataset requiring imputation. This process helps reflect the uncertainty inherent in the imputation.

This approach offers several critical advantages for microdata imputation, and wealth imputation more specifically:

1. **Distribution preservation**: By modeling the entire conditional distribution, QRF is adept at capturing and preserving the right-skewness and heavy tails characteristic of wealth distributions (Meinshausen and Ridgeway, 2006).

2. **Non-linear relationship handling**: The tree-based structure of RF, and thus QRF, automatically handles complex non-linear relationships between predictors (e.g., demographic variables) and the imputation target (e.g., wealth) without requiring explicit transformation or pre-specification of these functional forms (Tang and Ishwaran, 2017).

3. **Automatic interaction detection**: QRF naturally incorporates interactions between predictor variables, as tree splitting rules inherently consider combinations of features (Tang and Ishwaran, 2017).

4. **Robustness to outliers**: The ensemble nature of random forests and the focus on quantiles (rather than just the mean) make QRF less sensitive to extreme outliers in the donor data that might distort parametric models (Learneconometricsfast.com, 2025).

5. **Single model for all quantiles**: Unlike standard QR, which requires fitting separate models for different quantiles, QRF produces an estimate of the entire conditional distribution from a single trained model, making it computationally more efficient for obtaining a comprehensive distributional picture (Meinshausen and Ridgeway, 2006).

When imputing from a survey with specific design features to a more general survey with somewhat different distributional properties, QRF's ability to learn localized relationships in the predictor space can be advantageous. If survey weights from the donor are incorporated during the QRF training (e.g., by influencing tree construction or the sampling of observations for bootstrap aggregation), the model can learn to represent the oversampled segments appropriately. The subsequent prediction onto the receiver dataset, which has its distinct sample structure, then relies on the learned conditional distributions. The challenge lies in ensuring that the relationships learned from the donor are transportable and applicable to the recipient, and that the resulting imputations in the recipient dataset, when combined with its own survey weights, yield valid population estimates. While QRF itself doesn't explicitly model survey design features like clustering or stratification in a formal statistical sense unless specifically adapted, its flexibility in capturing complex data structures can implicitly handle some of the heterogeneity introduced by such designs (Hao and Naiman, 2007), making it much stronger than other more limited imputation approaches.

Nonetheless, QRF has its own limitations. Given the data-splitting nature of a tree, certain terminal nodes may receive a single or very few extreme training samples. When imputing, all the data points from the receiver dataset that land on those leaves will likely receive the same or very similar values for the imputed variable, even if there are differences in predictor values between them. In practice, this means that if the donor and receiver datasets have distributional differences, imputations at the extreme tails of the receiver dataset may suffer. Data points that are not necessarily unusual or extreme might receive extreme imputations, while truly extreme values in the receiver dataset are at risk of not being regarded as so if the donor dataset had a narrower range.

3 Data

3.1 Survey of Consumer Finances

The Survey of Consumer Finances (SCF), sponsored by the Federal Reserve Board, is a triennial survey providing detailed information on U.S. households' assets, liabilities, income, and demographic characteristics. Its dual-frame sample design includes a standard national area-probability sample and a list sample deliberately oversampling wealthy households to better capture the skewed wealth distribution (Barceló, 2006). The SCF is a benchmark for wealth imputation research due to its detailed financial data and the known complexities arising from its design and the nature of wealth. The public-use SCF datasets are themselves multiply imputed by the Federal Reserve to address item nonresponse (Barceló, 2008).

3.2 Current Population Survey

The Current Population Survey (CPS), conducted by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics, is a monthly survey primarily focused on labor market information. The Annual Social and Economic Supplement (ASEC) collects detailed annual income data and some information on assets and liabilities, though far less comprehensively than the SCF. The CPS uses a national probability sample and is a key source for income and poverty statistics. Missing data, particularly for income items, is also a feature of the CPS.

3.3 Comparative analysis and characteristics for imputation

Beyond wealth data's inherent challenges, imputing between SCF and CPS presents additional complications due to their differences in scope, design, and wealth data measurement.

1. **Sampling approach**: The SCF employs a dual-frame sample design, deliberately oversampling wealthy households through a list sample derived from tax returns. The CPS uses a more standard probability sample that does not effectively capture the upper tail of the wealth distribution (Bryant, 2023).

2. **Sample size and frequency**: The SCF typically includes about 4,500-6,000 households and is conducted triennially, while the CPS surveys approximately 60,000 households monthly.

3. **Wealth variable coverage**: The SCF collects extremely detailed information on financial assets and liabilities, while the CPS lacks this granularity, making direct matching of asset categories difficult.

These structural differences create substantial challenges for transferring wealth information between the surveys whilst maintaining the statistical integrity of the resulting dataset.

4 Methodology

4.1 Microimpute package implementation

Microimpute is PolicyEngine's specialized Python framework that enables variable imputation through multiple statistical methods, providing a consistent interface for comparing and benchmarking different imputation approaches using quantile loss calculations.

4.1.1 Core capabilities

The package currently supports four primary imputation methods: Statistical Matching, Ordinary Least Squares Linear Regression, Quantile Regression Forests (QRF), and Quantile Regression. This multi-method approach allows researchers to systematically evaluate which technique provides the most accurate results for their specific dataset and research objectives.

4.1.2 Key features for microimputation

Microimpute addresses imputation challenges between complex survey datasets through several specialized features:

1. **Survey data weights integration**: Handles survey data weights through sampling to ensure that models are trained on a donor data set representative of the true distribution.

2. **Method comparison and benchmarking**: The framework allows researchers to easily compare different approaches and automatically determine the method providing the most accurate results.

3. **Flexible methodological set-up**: Enables advanced usage through specified hyperparameter setting and tuning.

4. **Quantile-based evaluation**: Uses quantile loss calculations to assess imputation quality across different parts of the distribution.

5. **Autoimputation**: Provides an integrated imputation pipeline that tunes method hyperparameters to the specific datasets, compares methods, and selects the best-performing to conduct the requested imputation in a single function call.

4.1.3 Implementation details

Microimpute's QRF implementation extends scikit-learn's Random Forest to provide full conditional quantile estimation, enabling stochastic imputation that preserves distributional properties rather than relying solely on point estimates.

Complete documentation, implementation details, and usage examples are available at https://policyengine.github.io/microimpute/.

5 Results

5.1 Evaluation metrics

To properly assess imputation quality for wealth data, we employ quantile loss to evaluate performance across quantiles. Quantile (or pinball) loss evaluates how well a model predicts a chosen conditional quantile by assigning an asymmetric penalty that depends on the sign of the forecast error and the target quantile. Formally, for residual $e_i = y_i - \hat{y}_i$ and quantile level $\tau \in (0, 1)$, the loss is

$$L_\tau(e_i) = \max\bigl(\tau\, e_i,\ (\tau - 1)\, e_i\bigr);$$

thus, under-prediction of an upper-tail quantile (large positive e_i) is penalized at rate τ, whereas over-prediction is penalized at rate $\tau - 1$. Minimising this piece-wise linear function ensures that, in expectation, exactly τ percent of true outcomes fall below the model's prediction, giving the estimator its distribution-calibrating property first formalised by Koenker and Bassett (Koenker and Bassett, 1978). Because the weights differ for positive versus negative errors, quantile loss captures directional bias. This is a crucial feature when imputing highly skewed variables like wealth, where large under-estimates in the right tail must be discouraged more strongly than equal-sized over-estimates. Compared with mean-squared or mean-absolute error, which optimise the conditional mean or median and penalise errors symmetrically, quantile loss directly targets the entire conditional distribution and remains robust to outliers, making it the appropriate metric for assessing the performance of imputation models when distribution-awareness is a priority (Ghenis, 2018).

Additionally, we ensure that the resulting wealth distributions resemble that of the donor wealth distribution in the SCF. The SCF includes household weights to quantify how representative each recorded household and its data are. Thus, by sampling the SCF distribution according to its weights, we can get a rough estimate of the true US wealth distribution, which simultaneously serves as a visual check for imputed wealth distributions.

Lastly, by evaluating the average wealth by disposable income decile that results from each method's imputations, we can attest that wealth correlates with income as expected, with households that have the highest disposable income also having the highest wealth.

5.2 Experimental setup

Using Microimpute's `autoimpute` function, we evaluate QRF against OLS, standard Quantile Regression, and hot deck Matching in net worth imputation. To create a ground truth for evaluation, we employ cross-validation, splitting the SCF into 5 folds, or subsets. For each model at a time, we:

1. Mask the wealth values of one holdout subset at a time
2. Tune the hyperparameters of those models that have a flexible set-up to the SCF data set, namely Matching and QRF
   (a) SCF survey data weights are passed into `autoimpute` for stratified sampling
3. Impute wealth onto the SCF holdout set using each method with the remaining four folds as the training data
   (a) Demographic and financial variables available in both surveys behave as predictors
   (b) Each model performs imputation at 20 equally spaced quantiles
4. Compare the imputed values to the SCF training values, measuring quantile loss at each of the imputation quantiles
5. Average quantile loss across all folds and quantiles

This approach allows for direct comparison between methods on a common testing framework, providing a robust assessment of relative performance. The model with the lowest average quantile loss is chosen as the best performing and automatically selected to perform the final imputation onto the CPS data set, for which the full SCF will be used for training.

Next, the imputation from the SCF onto the CPS is replicated for the other three models that were not selected, with an identical setup that includes training on the full SCF, the same predictor variables, and imputations at the median quantile, avoiding introducing any bias toward a specific side of the distribution.

5.3 Imputation results

The cross-validation results demonstrate QRF's superior performance across the wealth distribution. QRF achieved an average quantile loss of 0.059 across all quantiles, outperforming OLS (0.075), hot deck Matching (0.076), and standard Quantile Regression (0.063). This 21-22% improvement over OLS and Matching and 6% improvement over Quantile Regression represents a substantial gain in imputation accuracy.

The performance advantage was particularly pronounced in the middle and upper-middle portions of the distribution (20th-80th percentiles), where QRF maintained consistently low quantile loss values between 0.07-0.09. While Quantile Regression showed competitive performance at extreme quantiles (above the 85th percentile), QRF's overall consistency across the entire distribution made it the optimal choice for wealth imputation.

Microimpute's automated hyperparameter tuning contributed significantly to these results. The optimal QRF configuration identified through cross-validation included 200 trees and a minimum of 5 samples per leaf node for a split. These parameters balanced model complexity with generalization capability, preventing overfitting while capturing the nuanced relationships between demographic predictors and wealth outcomes.

5.3.1 Quantile loss

Comparing all four models to each other, we can evaluate performance through quantile loss, as well as comparing the overlap of the imputed wealth distribution with the original SCF data.

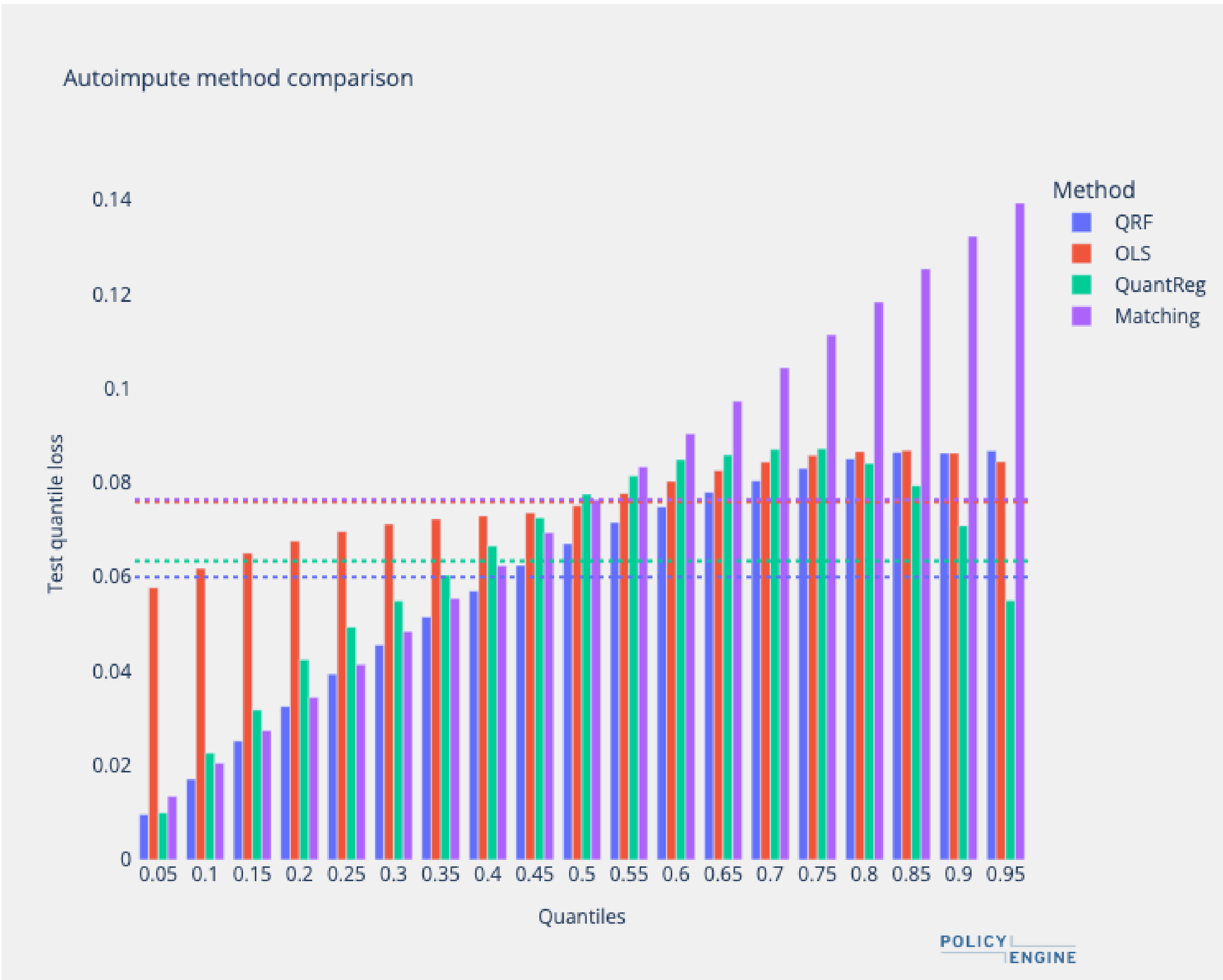

Figure 1: Cross-validation method performance at 20 equally spaced quantiles. Test quantile loss at each quantile is averaged across 5 cross-validation folds, and the dashed lines represent average quantile loss across all quantiles.

5.3.2 Imputed wealth distribution comparisons

We observe how QRF proves to be the best-performing model out of the four. It significantly outperforms Matching and OLS on average, while only being outperformed by QuantReg past the 80th quantile. Matching's performance presents the perfect opportunity to see the quantile loss's directional bias at work. Because Matching does not incorporate quantile information into its imputation process in any way, it will match donor and receiver units, and thus impute values identically regardless of the quantile at work. The laddering behavior observed above results from the fact that Matching's wealth imputations consistently underpredict relative to the true wealth values, and this property is increasingly favored for quantiles below the median, and increasingly penalized as quantiles approach the right end of the distribution.

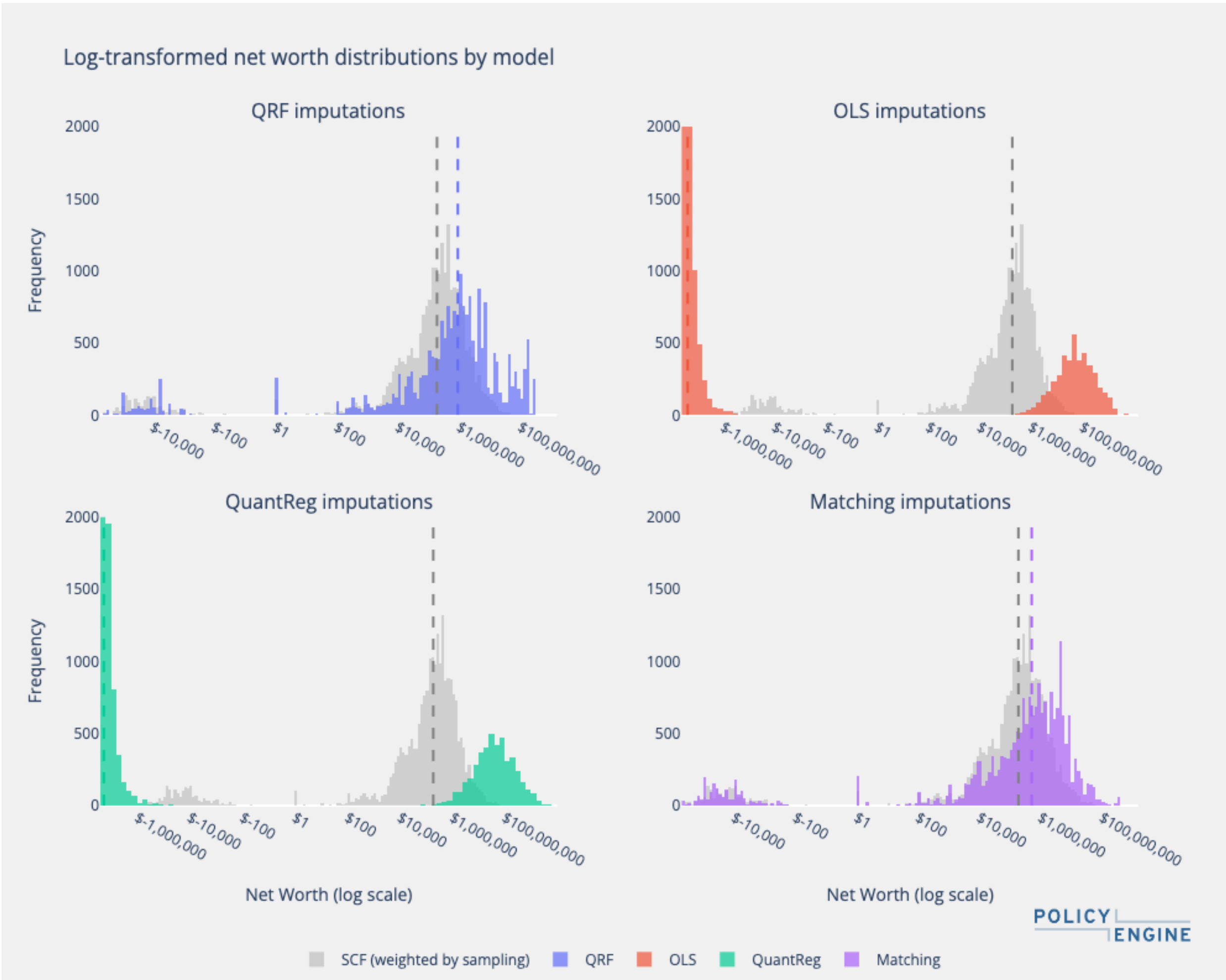

Figure 2: Weight-adjusted imputed wealth distributions model comparisons, relative to the donor SCF wealth distribution. Dashed lines represent median values.

By visually comparing the wealth distributions resulting from imputing with each method, and comparing them to the weighted donor distribution, we gain a more comprehensive understanding of imputation performance, moving past the test quantile loss average measured on the SCF.

5.3.3 Distribution of wealth by disposable income decile

These results support the observations above, with QRF presenting the most consistent and plausible relationship to disposable income, with a gradually increasing average as the deciles

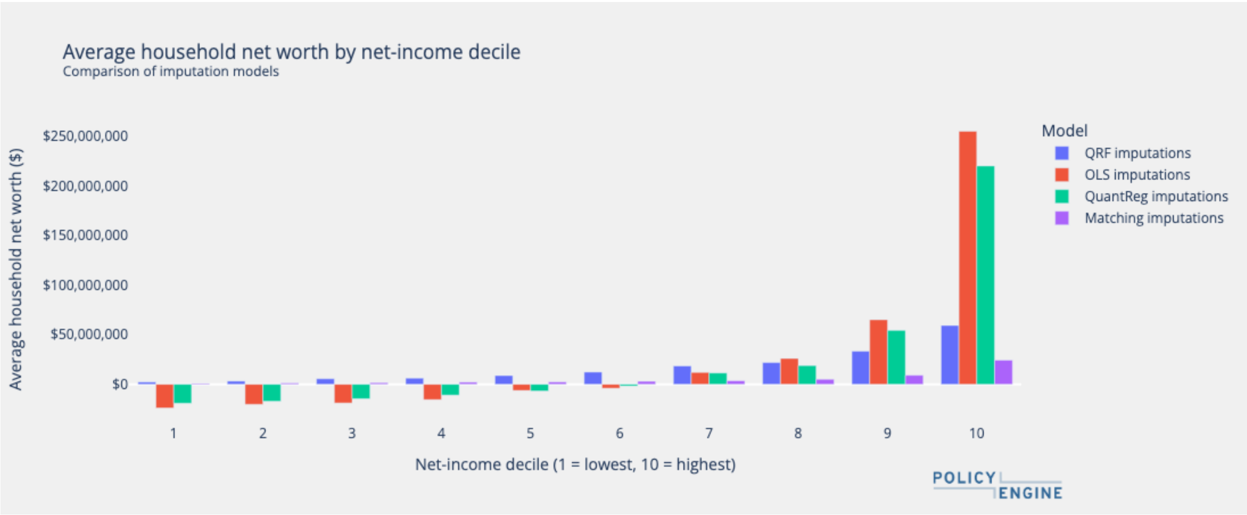

Figure 3: Average household net worth by disposable income decile model comparison. Households are divided into 10 equally sized groups based on their disposable income.

increase. This plot also demonstrates the caveats of the other models, showing the extreme negative and positive predictions that OLS and QuantReg produce at the left and right tails, respectively, and Matching's underprediction at every decile.

6 Discussion

This paper has demonstrated both theoretically and empirically that Quantile Regression Forests provide substantial advantages for microimputation, particularly through the example of wealth imputation from the SCF to the CPS. By preserving the full conditional distribution of wealth, QRF maintains the critical statistical properties of wealth data that traditional methods fail to capture.

6.1 Strengths powered by Microimpute

The Microimpute package's design philosophy and implementation choices provide several key advantages that contributed to the success of our wealth imputation analysis:

1. **Unified interface for method comparison**: Microimpute's consistent API across all imputation methods enabled systematic benchmarking without implementation-specific biases. This standardization ensures that performance differences reflect genuine methodological advantages rather than implementation artifacts (PolicyEngine, 2025).

2. **Automated method selection**: The package's `autoimpute` function streamlines the imputation workflow by automatically comparing methods and selecting the best performer based on quantile loss metrics. This feature proved particularly valuable given the wealth data's complexity, as it removed subjective method selection and ensured optimal performance.

3. **Survey weight integration**: Microimpute's native support for survey weights through stratified sampling ensures that imputation models properly represent population distributions. This capability is crucial when transferring information between surveys with different sampling designs, such as the SCF's oversampling of wealthy households.

4. **Survey data weights integration**: By implementing quantile loss as the primary evaluation metric, Microimpute directly addresses the challenges of skewed distributions. This metric's asymmetric penalty structure naturally prioritizes accurate imputation at distribution tails, where traditional metrics like Root Mean Squared Error (RMSE) often fail.

5. **Computational efficiency**: The package's optimized implementation enables processing of large microdata files while maintaining reasonable computation times. Cross-validation on the full SCF dataset, including QRF hyperparameter tuning, was completed in under 30 minutes on standard hardware, making iterative experimentation feasible.

6. **Open-source transparency**: As an open-source tool, Microimpute allows full inspection and modification of imputation algorithms, promoting reproducibility and enabling custom extensions for specific research needs (PolicyEngine, 2025).

6.2 Limitations and future improvements

Despite the demonstrated advantages, several limitations warrant consideration for future development:

Current Package Limitations: While Microimpute currently supports four imputation methods, expanding to include modern machine learning approaches such as neural networks, gradient boosting machines, or deep learning architectures could further improve performance, particularly for complex multivariate relationships (Alaa et al., 2024). The package would benefit from implementing ensemble methods that combine multiple imputation approaches, potentially leveraging the strengths of different methods across different parts of the distribution. Moreover, additional evaluation metrics to quantile loss would enhance model selection and assessment, ensuring a thorough understanding of each model's behavior at every step.

QRF-Specific Challenges: The terminal node sparsity issue identified in Section 2.2.4 remains a fundamental limitation of tree-based methods. When few training samples reach certain terminal nodes, multiple observations in the recipient dataset may receive identical imputed values, potentially underestimating variability in extreme wealth categories. Future work could explore adaptive tree construction methods that ensure minimum node occupancy or hybrid approaches that combine QRF with parametric methods at distribution extremes.

These enhancements would position Microimpute as a comprehensive solution for survey data imputation challenges while maintaining its current strengths in ease of use and methodological rigor.

7 Conclusion

This paper has reviewed methodological advances in microdata imputation, focusing on techniques suitable for complex survey data like wealth. We highlighted the limitations of traditional methods and the promise of advanced approaches, particularly Quantile Regression Forests, for handling skewed distributions and non-linearities.

The key contributions of this work are the synthesis of current knowledge on imputation for challenging microdata, a detailed examination of QRF's suitability, and an introduction to the Microimpute package. Our review suggests that QRF represents a significant step forward in preserving the statistical integrity of imputed microdata, crucial for robust economic and social analysis. The implementation of QRF in the Microimpute package provides a practical tool for researchers seeking to combine detailed microdata across datasets.

Future research should continue to refine QRF for imputation, particularly in response to challenges like limited data at extreme quantiles. Comparative studies against other emerging techniques, like deep learning models (Alaa et al., 2024), are also vital. Continued innovation in imputation methodology is fundamental to the integrity of evidence-based research and policymaking.

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