channels allow for an increase in the relative wealth position conditional on the size of either component and the underlying circumstances of wealth accumulation. The former condition is trivial in its nature but subject to a number of constraints which may influence the magnitude of the contribution to net worth. These circumstances include a variety of socio-economic parameters, reaching from the arrangement of tax and welfare systems to cultural aspects shaping consumption and savings patterns (Fessler and Schürz, 2015). In addition to this aspect, earnings uncertainty may also have a significant impact upon the savings pattern over the lifecycle (Irvine and Wang, 2001).

Analyzing transfer wealth entails the challenge of conceptually defining transfers versus self-made wealth, which also caused a lively debate between Kotlikoff (1988) and Modigliani (1988). There is no consensus on whether returns to inherited wealth are counted as transfer wealth or as life-cycle wealth. In addition, inheritances and inter vivos gifts normally do not cover implicit gifts like appointing an offspring as an equal partner in a lucrative family business or paying the costs for college education. Moreover, meeting the costs of food and clothing for dependents is not considered a gift but as provisioning for the family.

In this paper, we pursue an econometric approach to assess the relative role of bequests and income for private household wealth. With harmonized survey data, we calculate cross-country estimates for the impact of inheritances on the likelihood of being at the top of the Eurozone wealth distribution. Similar calculations have been carried out by Fessler and Schürz (2015), however, merely by means of OLS estimations. We extend existing research using quantile regressions to calculate non-linear elasticities between the distribution of earned income (wages and earnings from self-employment) and inheritances, and the distribution of net household wealth. Section 2 therefore provides our methodological approach of multivariate quantile regressions. In section 3, we describe the survey data and address considerations concerning cross-country comparability of wealth data. We then present the results in section 4. First, we show how country shares in the Eurozone top wealth percentiles are associated with the receipt of bequests. Thereafter, the results of the quantile regressions allow to compare the influence of income versus inheritances on climbing in the net wealth distribution. Finally, section 5 draws some concluding remarks.

2 Methodological Approach: Quantile Regression

Linear regressions are useful to gain first insights into the data and the relationships between variables. Especially with wealth and income data these are, however, only rough approximations to the truth. This is due to the fact that the conditional mean is a bad approximation for very skewed distributions such as for wealth and income. One method commonly applied to model such responses is quantile regression, which was originally used as a robust method of estimation when the normality assumption was not strictly satisfied. This will especially be the case if unobservable constituents (Koenker and Bassett, 1978) influence the conditional distribution of the variable regressed on. In wealth regressions, this can be considered a severe problem, since the
additional information included in micro datasets is often limited. This is true for, e.g., abstract concepts like power-relations, which arguably vary along the distribution and are hardly captured by additional regressors.

Quantile regression limits the influence of these effects since it regresses on the mean but conditionally on a given quantile, so that outliers have little effect on the estimate. In the context of wealth analyses, we apply this method to regress certain individual- and household-level characteristics on quantiles of the net wealth cumulative distribution function (CDF). Let $Y$ be a random variable with the cumulative distribution function,

$$F(y) = P(Y \leq y)$$

then we can write the quantile function for a quantile $\tau \in [0,1]$ as an inverse function,

$$Q(\tau) = F^{-1}(\tau) = \inf(y : F(y) \geq \tau)$$

As proposed by Koenker and Bassett (1978), the $\tau$th quantile of such a random sample $\{y_1, y_2, \ldots, y_n\}$ can be calculated as

$$\min_{\xi \in R} \sum_{i=1}^{n} \rho_\tau(y_i - \xi)$$  \hspace{1cm} (1)

where $\rho_\tau(\cdot)$ is a so-called check function. This function is based on the absolute deviations of the residuals $|y_i - \xi|$ which are weighted by $\tau$ if the term is positive and by $(1 - \tau)$ if it is negative. Hence $\rho_\tau = \tau \cdot I(y_i > \xi) + (1 - \tau) \cdot I(y_i < \xi)$. Analogue to the estimation of the unconditional mean for a random sample which minimizes the sum of squared residuals, this applies to the linear conditional mean function $E(Y | X = x) = x^T \beta$ by solving

$$\hat{\beta} = \arg \min_{\beta \in \mathbb{R}^p} \sum_{i=1}^{n} (y_i - x_i^T \beta)^2$$  \hspace{1cm} (2)

Given the linear conditional quantile function $Q(\tau | X = x) = x_i^T \beta(\tau)$, we estimate

$$\hat{\beta}(\tau) = \arg \min_{\beta \in \mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^T \beta)$$  \hspace{1cm} (3)

This implies that the estimator is a general case of Least Absolute Deviations estimator (LAD), which regresses on the median, shifted by a factor $\rho_\tau$. 
